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Modeling Energy-Environment-Economy Interrelations

Edited by
George Halkos

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About the Editor

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George E. Halkos (BA, MSc, PhD) is a Professor of the Economics of Natural Resources in the Department of Economics at the University of Thessaly. He has worked as a team leader and research fellow in various research and academic institutions. In addition, he has participated in and presented articles at International Conferences and acts as a referee for many scientific journals. His research interests include applied statistics and econometrics, simulations of economic modeling, natural resource and environmental economics, applied micro-economics with emphasis in welfare economics, air pollution, game theory, and mathematical models (non-linear programming).

Preface to “Modeling Energy– Environment–Economy Interrelations"

This Special Issue examines the nexus between economic growth, energy consumption, and the environment. Our industrialized world depends on fossil fuels to meet its energy needs, and since fossil fuels are associated with both economic growth and severe environmental degradation, the associations between air pollutants emissions, energy consumption and economic growth must be examined. Additionally, CO_2 emissions are forecasted at the Global Level, and the determinants of renewable energy consumption are discussed, along with an assessment of the economic and environmental impacts of alternative renewable portfolio standards and the possible winners and losers. There is particular emphasis on assessing fossil fuels and renewables' effect on energy poverty conditions in Europe. The findings of this Special Issue will be invaluable to researchers and policy makers.

George Halkos
Editor

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Article

Examining the Linkages among Carbon Dioxide Emissions, Electricity Production and Economic Growth in Different Income Levels

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Abstract: Our industrialized world highly depends on fossil fuels to cover its energy needs. Although fossil fuels have been linked with economic growth, their use has also been found to have severe impacts on the environment. The linkages among carbon dioxide emissions, energy consumption and economic growth have been extensively examined in the current literature. The present study focuses on electricity production from fossil fuels, as well as from renewable sources and examines their linkages with CO_2 emissions and economic growth in 119 world countries of different income levels, by assessing Granger causality. In addition, the Environmental Kuznets Curve (EKC) hypothesis is tested, in order to evaluate whether economic growth and carbon dioxide emissions are linked with an inverse U-shaped relationship and with an N-shape relationship in higher income levels. The EKC hypothesis is confirmed for high income and upper-middle income countries, but not for lower-middle and low income levels and a bidirectional Granger causality is found between GDP per capita and CO_2 per capita in all income levels.

Keywords: CO_2 emissions; electricity production; Environmental Kuznets Curve; fossil fuels; renewables; economic growth; income levels

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1. Introduction

The rapid economic growth that followed the industrial revolution had a major impact on the environment. Fossil fuels were the core of the new industrialized world and their use started growing rapidly, reaching millions of tons of oil equivalents by today [1]. This excessive use and burning led to the emission of greenhouse gases (GHG) into the atmosphere which, in large amounts, contribute to global warming and climate change [2].

Carbon dioxide (CO_2) emissions are the number one anthropogenic contributor to climate change, since they constitute 81% of total GHG emissions for 2018. At the same time, CO_2 emissions that come from fossil fuel and industrial processes constitute 65% of total GHG emissions (according to 2010 data) [3]. These emissions are expected to increase even more: global population is expected to rise to approximately 9 billion by 2050 [4] and, therefore, world energy consumption is expected to rise nearly 50% between 2018–2050 [5].

In 1992, the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol in 1997, made it obvious that, in order to avoid a disastrous effect on the environment, it is essential to reduce the world's GHG emissions to a large extent [2]. Even so, according to recent data, there seems to be a 61.62% increase of total CO_2 emissions (kt) in the world from 1990 until 2016 [6]. At the same time, fossil fuel energy consumption, as a percentage of total energy use, has not changed significantly and energy use (kg of oil equivalent per capita) has increased by 15.6% in the period 1990–2014 [7]. All these data emphasize the urgent need to implement CO_2 emissions reduction measures, by limiting the use of fossil fuels and switching to renewable energy sources instead [8].

Energy consumption seems to be the main cause of the large CO_2 emissions. At the same time, higher energy consumption leads to higher economic development [9].

According to Adams et al. [10], if non-renewable energy consumption increases by 10%, economic growth will increase by 2.11%, but if renewable energy consumption increases by 10%, economic growth will increase by 0.27%. This is why many scientists argue that a reduction in CO_2 would have a negative outcome for economic growth, something that would be an undesired result in developed and, especially, in developing countries [9]. The links and the relationship between energy consumption, CO_2 emissions and economic development have been intensively studied in the last decades [11].

The linkages among CO_2 emissions and electricity production have not been widely examined in the current literature. This study aims to contribute to the existing literature and examines the causality among economic growth, electricity production and CO_2 emissions in 119 world countries, categorized by income status (high, upper-middle, and lower-middle and low income), over the period of 2000–2018. Countries of different income levels are expected to have substantial differences regarding the relationships that exist among these factors and their identification is significantly important, since it can provide a better understanding and important knowledge for policy makers, in order to implement targeted measures for an efficient energy transition and the achievement of global sustainability. This study examines and assesses all these different linkages, for a large number of world countries classified by income with recent data, something that has not been widely investigated in the current literature. To achieve that, panel data are collected and the linkages between CO_2 emissions, electricity production from fossil fuels, electricity production from renewable sources and GDP per capita are investigated, while taking into consideration population density as well. Static and dynamic regression models are constructed, an in-depth econometric analysis is conducted, the Environmental Kuznets Curve is assessed for each income level and Granger causality is tested.

The paper is organized as follows: Section 2 presents recent economic and energy data, as well as data regarding CO_2 emissions that come from different energy sources. Section 3 includes an in-depth literature review on the examined field and Section 4 presents used data and methodology. In Section 5, the results are presented and in Section 6 the results are discussed. Section 7 concludes the paper.

2. Recent World Data

The world's GDP has increased rapidly over the last twenty years, from \$33.624 trillion in 2000 to \$87.799 trillion in 2019 (Figure 1), according to the World Bank database [12]. Over the same time period, global population increased from 6.114 billion in 2000 to 7.674 billion in 2019 [13], meaning that GDP per capita increased from \$5499.151 in 2000 to \$11,441.733 in 2019 [14].

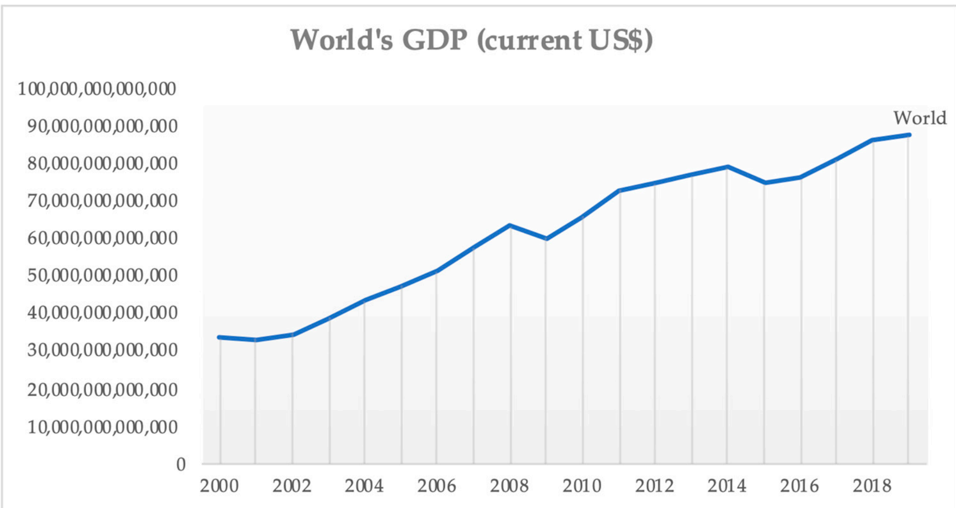


Figure 1. World's GDP (current US$) (Data source: World Bank [12]).

Focusing on the energy sector, world's total final energy consumption reached 9,937,702 kilotonnes of oil equivalent in 2018 [15]. The industrial sector and the transportation sector were the highest consumers of world's total energy supply (Figure 2) and fossil fuels were energy's main provider. According to IEA data [16], in 2017, the share of renewables in world's final energy consumption was estimated at 17.3%. The residential sector was the highest consumer of renewable energy supply (Figure 3).

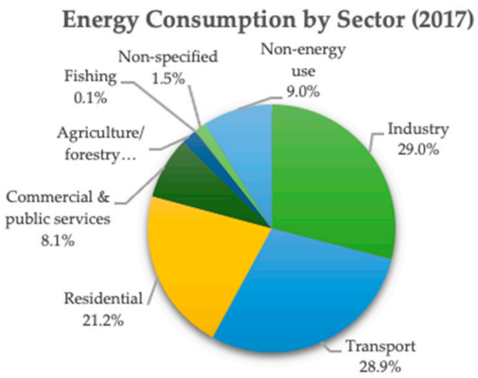


Figure 2. Energy Consumption by Sector in 2017 (Data source: IEA [15]).

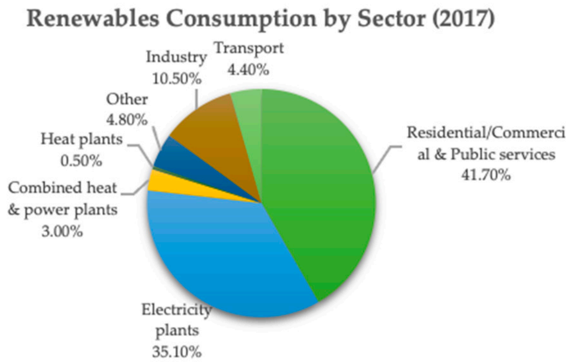


Figure 3. Renewables Consumption by Sector in 2017 (Data source: IEA [16]).

World's total CO_2 emissions reached 33,513.3 Mt of CO_2 in 2018 [17], estimating thus the per capita emissions at 4.4 tonnes CO_2 [18]). Coal was the energy source that was responsible for most of energy-related CO_2 emissions in the world, while oil followed [19] (Figure 4). In addition, world's total forest area has decreased over the last two decades; from 40,556,022.3 km^2 in 2000, it decreased to 39,958,245.9 km^2 in 2016, according to the World Bank database [20].

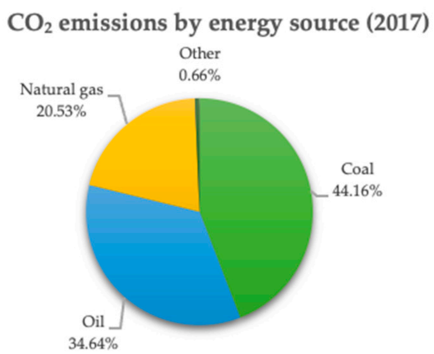


Figure 4. CO_2 emissions by energy source in 2017 (Data source: IEA [17]).

3. Literature Review

The existing literature about links and relationships between energy consumption, environmental pollution and economic growth is divided into three categories. The first category concerns the investigation of the CO_2 Environmental Kuznets Curve hypothesis. According to the EKC hypothesis, environmental pressure in an economy starts growing as the income grows, reaches a peak and, after a certain level of income, starts reducing [21]. This happens because, as a nation tries to develop, uses its natural resources with no concerning on the environmental degradation; after a certain income level, and since environmental degradation can lead to various problems, nations focus on improving environmental quality and protecting the environment [22]. Based on the EKC hypothesis, an inverted U-shaped relationship exists between economic development and environmental degradation. For high income countries, the EKC hypothesis has a cubic and not a quadratic form and an N-type curve is observed, indicating that even higher levels of GDP per capita lead to an increase of environmental degradation [23]. The EKC has significant implications for sustainability [24].

A plethora of studies have been carried out in which this hypothesis is tested, starting from 1991 and the empirical study by Grossman and Krueger [9]. A variety of recent studies have examined and evidenced the CO_2 EKC hypothesis for various different regions [25–30]; in contrast, some recent studies that have found that the EKC hypothesis wasn't valid for certain regions also exist in the literature [31–34].

The second category concerns the research of causality among economic growth and energy consumption. These studies examine the hypothesis that growth in economy is related to growth in energy use and they test that relationship using time series models, usually with Granger causality and cointegration models. Mehrara [35], Narayan and Smyth [36], Apergis and Payne [37], Ozturk et al. [38] and Apergis and Payne [39], among others, have examined this hypothesis.

The third category combines the previous two categories by examining the relationship among economic growth, energy consumption (renewable and non-renewable), CO_2 emissions and other variables (urbanization, trade, etc.). These studies examine the argument that economic growth has a long-term influence on energy consumption and pollution growth [9]. Wang et al. [40] have found a bidirectional causality between CO_2 emissions and energy consumption and between economic growth and energy consumption among 28 provinces in China, while energy consumption and economic growth are found to be the cause for CO_2 emissions in the long run. Lu [41] has also reached the same results in his study for 24 Asian countries. Lin and Moubarak [42], in their study for China, have found a bidirectional causality between renewable energy consumption and economic growth, although they found no causality between carbon emissions and renewable energy consumption. Pao and Tsai [43] have evidenced a bidirectional causality between income, energy consumption and emissions in Brazil, while Pao et al. [44] have found the same results for Russia. In contrast, Lotfalipour et al. [9] in their study on Iran, found a unidirectional causality from economic growth to CO_2 emissions and no causality from fossil fuels consumption to CO_2 emissions. Also, Soytas et al. [45] in their study for the United States, found no Granger causality between income and CO_2 emissions and between energy use and income.

Some recent studies have been focusing specifically on European countries and the relationship between economic growth, energy consumption and carbon emissions that exists. Examples of those studies include the following: Acaravci and Ozturk [46] examined these relationships for 19 European countries and found a long run relationship between CO_2 emissions, energy consumption and economic growth only for specific countries. They also confirmed the EKC hypothesis in Denmark and Italy. Pirlogea and Cicea [47] also examined the links between energy consumption and economic growth and found that there is a unidirectional causality from renewable energy consumption to economic growth in Romania and from energy consumption (natural gas) to economic growth in Spain on short-run, concluding that there is a long run equilibrium between economic growth and energy consumption in every EU country. Bölük and Mert [11] have tested the EKC hypothesis in 16 EU countries and they concluded that the EKC hypothesis was not valid in these countries. Kasman and Duman [48] examined the causality among energy consumption, economic growth, CO_2 emissions, taking also into consideration the trade openness and urbanization, for 15 European countries. They provided evidence that support the EKC hypothesis and they found a unidirectional causality from energy consumption, trade openness and urbanization to CO_2 emissions, among others. Alper and Oguz [49] examined the relationship between economic growth, renewable energy consumption, capital and labor for six EU countries and concluded that renewable energy consumption has a positive impact on economic growth for all 6 countries.

The examination of the Energy-Environmental Kuznets Curve (EEKC) has also been a topic of interest in the literature and has been assessed on a global and regional scale. More specifically, various studies have been focusing on the examination of the linkages that exist between economic growth and energy consumption. Some studies have managed to confirm the existence of the EEKC globally and regionally [50–52], while a plethora of studies exist that could not confirm the hypothesis [53–55].

Regarding the linkages that exist among CO_2 emissions, electricity production and economic growth, fewer studies have been focusing on that. For instance, in a recent study for Ghana, it was found that a bidirectional causality exists from hydroelectric sources' electricity production to CO_2 emissions, while a unidirectional causality is found from CO_2 emissions to renewables and waste energy production, as well as from CO_2 emissions to fossil fuels electricity production (oil, gas and coal), among others [56]. For the case of Pakistan, it was found that, among others, a weak unidirectional causality exists from CO_2 emissions to electricity production, both from natural gas and oil [57]. Focusing on Europe, and more specifically on the case of Italy, the EKC hypothesis has been validated, while it has been found that in fact electricity production per capita that comes from renewable sources can lead to a reduction of CO_2 emissions per capita, both short-term and long-term [58].

Only a few studies in the literature have studied these linkages and have tested the EKC hypothesis for different income levels. For example, Al-Mulali et al. [59] investigated the EKC hypothesis for different income groups, while taking into consideration the Ecological Footprint instead of CO_2 emissions to stand for environmental degradation. The authors confirmed the EKC hypothesis only for high income and upper-middle income countries, while the hypothesis was not valid for lower-middle and low incomes. Similarly, Ulucak and Bilgili [60] followed a similar approach, using the Ecological Footprint and classifying the studied countries by income. The authors confirmed the EKC hypothesis for all income levels. In addition, Aruga [52] examined the EEKC hypothesis for 19 Asia-Pacific countries, depending on income, and the results indicated that the EEKC hypothesis was confirmed only for high income countries, and not for low and middle income.

As it is highlighted, there is a plethora of studies that examine the causality among economic growth, energy consumption and carbon dioxide emissions, using different econometric procedures and techniques and their results differ substantially. This study aims to provide a comprehensive approach with recent data, focusing specifically on electricity production and including 119 world countries categorized by income level, assessing thus the different relationships that exist among these factors in different income groups. The study contributes to the existing literature, by combining all the above elements with an in-depth econometric analysis that is followed.

4. Materials and Methods

4.1. Data

Panel data were collected from the International Energy Agency (IEA) and the World Bank Database for 119 world countries and for the period 2000–2018. These countries were categorized based on their income level, as it has been identified by the World Bank, that takes into consideration GNI per capita (current USD) to divide the countries to four different income groups. The newest classifications were set on July 2020 and the thresholds are presented in Table 1 [61]. The 119 countries for which data were collected and that were included in the analysis are presented in Figure 5, classified by income level: 47 countries are identified as high income countries, 33 as upper-middle income countries, 32 as lower-middle income countries and 7 as low income countries. The indicators for which data were extracted are presented in Table 2.

Table 1. Income classification thresholds, as set by the World Bank.

Income Level	Threshold (July 2020)
High income	>12,535
Upper-middle income	4046–12,535
Lower-middle income	1036–4045
Low income	<1036

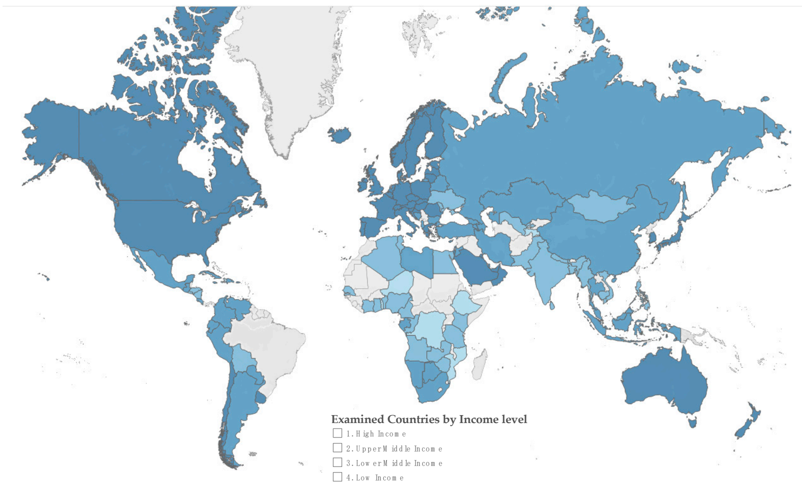


Figure 5. The 119 countries included in the analysis, by income level.

Table 2. Extracted indicators and data sources.

	Source	Indicator	Measurement
1	IEA [62]	Total electricity production	GWh
2	WB [13]	Population	total
3	WB [63]	Electricity production from oil, gas and coal sources	% of total
4	WB [64]	Electricity production from renewable sources, excluding hydroelectric	% of total
5	WB [65]	Electricity production from hydroelectric sources	% of total
6	WB [66]	CO_2 emissions	Metric tons per capita
7	WB [14]	GDP per capita	Current US$
8	WB [67]	Population density	People per sq. km of land area

Indicators 4&5 were combined, in order to create a variable that refers to electricity production from renewable sources, including hydroelectric. Indicators 1&2 were used to estimate electricity production per capita, so that electricity production from fossil fuels (*EPFpc*) and renewable sources (including hydroelectric) per capita (*EPRpc*) will be estimated, based on the indicators 3&4. Forecasts were provided, relying on exponential smoothing, in order to complete the missing data for the last few years wherever it was necessary. To achieve that, various forecast accuracy measures were examined, such as Mean Absolute Percentage Error—MAPE, Mean Square Deviation—MSD, etc.

4.2. Econometric Methodology

The EKC curve and the relationship and causality between CO_2 emissions and GDP, electricity production from fossil fuels per capita, electricity production from renewable sources per capita and population density were examined, based on the following methodology.

Before performing the regression analysis, several econometric tests are conducted to address different problems that might occur. A usual problem when working with panel data is variables' correlation; in order to determine if the time-series are cross-sectional independent, Pesaran's cross-section dependence test is used. OLS Dummy estimator (FEM) allowing for individual fixed effects with Driscoll-Kraay standard errors can assist in the correction of the variance-covariance matrix, in cases where the time series are found to be cross-sectional dependent. For Random Effects, Breusch-Pagan LM test for individual effects is applied and robust standard errors are required.

In cases where cross-section dependence is evidenced, unit root tests are performed. Dickey-Fuller and Augmented Dickey-Fuller tests can be performed when analyzing panel data, with the issue of homogeneity in the autoregressive parameter. Fisher type tests do not adopt this restrictive assumption and they don't require strongly balanced panels. The asymptotic behavior of the time series (T) and the cross-section dimensions (N) should be taken into consideration when performing unit root tests. Fisher type tests can be used in cases where T and N tend to infinity, but the number of panels with no unit root must raise at the same rate as N.

In cases of non-stationarity, panel cointegration tests are performed: more specifically, Westerlund test are performed to check for panel cointegration, based on the significance of the error correction term in the error correction model. Westerlund proposed four cointegration tests: the G_t and G_a statistics, which test the null hypothesis of no cointegration for all cross-sectional units, rejecting the hypothesis in cases of cointegration for at least one unit, and the P_t and the P_a statistics, which reject the hypothesis in cases of cointegration of the panel in total. In addition, the causal relationships among the studied factors are examined by conducting Granger causality tests. Granger causality can help identify whether the relationship between two variables is unidirectional, bidirectional or if no causality exists between them [68,69].

Three different data sets are constructed: one for high income countries (47 countries), one for upper-middle income countries (33 countries) and one for lower-middle & low income countries (39 countries). After the data collection, their combination and the extraction of the necessary variables, Box-Cox tests have been used, in order to test linear against logarithmic forms. Quadratic regression models, as well as a cubic regression model were constructed, in order to examine the linkages among the studied variables, considering CO_2 emissions per capita as a dependent variable and GDP per capita, per capita electricity production from fossil fuels, per capita electricity production from renewables and population density as independent variables. The general forms of these models are:

$$Y_{it} = a + X_{it}\beta_{it} + X_{it}^2\beta_{it} + \delta_i + \gamma_i + \varepsilon_{it} \quad (1)$$

$$Y_{it} = a + X_{it}\beta_{it} + X_{it}^2\beta_{it} + X_{it}^3\beta_{it} + \delta_i + \gamma_i + \varepsilon_{it} \quad (2)$$

where Y_{it} is the dependent variable, X_{it} an independent variables' k-vector, δ_i and γ_i the cross-section and period specific effects, that can be either fixed or random, and ε_{it} the disturbance terms. After modification, the proposed models that include only the statistically significant variables, become:

$$CO2pc_{it} = a + \beta_{1it}GDPpc_{it} + \beta_{2it}GDPpc_{it}^2 + \beta_{3it}EPFpc_{it} + \beta_{4it}EPRpc_{it} + \beta_{5it}Dens_{it} + \delta_i + \gamma_i + \varepsilon_{it} \quad (3)$$

$$CO2pc_{it} = a + \beta_{1it}GDPpc_{it} + \beta_{2it}GDPpc_{it}^2 + \beta_{3it}GDPpc_{it}^3 + \beta_{4it}EPFpc_{it} + \beta_{5it}EPRpc_{it} + \beta_{6it}Dens_{it} + \delta_i + \gamma_i + \varepsilon_{it} \quad (4)$$

In Equations (3) and (4), *CO2pc* stands for CO_2 emissions per capita, *GDPpc* for GDP per capita, *EPFpc* for electricity production from fossil fuels (oil, gas and coal) per capita, *EPRpc* for electricity production from renewable sources per capita (including hydroelectric) and *Dens* for population density.

To estimate the panel data models, the ordinary least squares (OLS) method was chosen and Fixed and Random Effects methods were applied; the choice of the appropriate method depends on the way that a_i is handled (fixed predefined number or random expulsion from a particular distribution). In the case of Random Effects, Hausman tests are also conducted, in order to check for inconsistencies in the RE estimations. The literature also suggests the use of fully modified ordinary least squares (FMOLS), a reliable non-parametric method that assists in tackling problems related to variables' endogeneity and serial correlation [70,71]. FMOLS estimators seem to perform significantly well in cases where the time series dimension is bigger than the cross sectional dimension [70]. In the present study, and since the cross sectional dimension is significantly bigger than the time series dimension, Fixed Effects with Driscoll-Kraay standard errors were chosen to be used, when modeling the static analysis. This way, the problem of cross-section dependence is prioritized and addressed.

In addition to the OLS method, and in order to capture the dynamic nature of the model, Generalized Method of Moments (GMM) was used for estimation, in terms of Orthogonal Deviations. GMM is used in statistical models in order to provide estimators for the parameters that are consistent, as well as asymptotically normally distributed [72]. It is a significantly important method for econometrics and is widely used in economics, since it can be applied in various models (linear/non-linear, cross-section, time series and panel data, etc.) [73]. In cases where moment conditions can be obtained, while the likelihood function cannot, GMM combines the moments and provides efficient estimators [74]. GMM assists in avoiding endogeneity, since it extends the static model, by including lagged variables that help control the problem, as well as in avoiding the problems of autocorrelation and reverse causation [75,76]. Due to the many advantages that come with its use, Generalized Method of Moments was chosen over dynamic ordinary least squares (DOLS), a parametric method that uses lagged terms and assists in endogeneity and serial correlation problems [77,78].

GMM minimizes the following Equation (5), regarding β:

$$M\ (\beta) = \left(\sum_{i=1}^{N} \Psi_i'\ u_i(\beta)\right) W \left(\sum_{i=1}^{N} \Psi_i'\ u_i(\beta)\right) = \zeta(\beta)' W \zeta(\beta) \tag{5}$$

In this equation, W is a pxp weighting matrix, Ψi is a $T_i xp$ instruments matrix for cross section i and $u_i(\beta) = (\Upsilon_i - f(X_{it}, \beta))$. White robust covariances are used to calculate the weighting of matrix W and the coefficient covariance estimates are:

$$\left(\frac{M^*}{M^* - k^*}\right) \left(\sum_t X_t' X_t\right)^{-1} \left(\sum_t X_t' \hat{u}_t \hat{u}_t{}' X_t\right) \left(\sum_t X_t' X_t\right)^{-1} \tag{6}$$

In Equation (6), M^* is the total number of stacked observations and k^* equals to the number of estimated parameters. According to Arellano and Bond [79], in orthogonal deviations each observation is seen as a deviation from the average of future observations and each deviation is weighted, in order to standardize the variance:

$$x_{it}^* = \left[x_{it} - \left(x_{i(t+1)} + \ldots + x_{iT}\right) / (T-t)\right] \sqrt{(T-t)} / \sqrt{T-t+1} \tag{7}$$

The (T_i-q) equations for individual unit (i) are:

$$Y_i = \delta w_i + d_i \eta_i + \nu_i \tag{8}$$

5. Results

5.1. Descriptive Statistical Analysis

The indicators presented in Table 2 were analyzed and combined, so that the necessary variables could be extracted, such as per capita electricity production from fossil fuels and from renewable sources. Table 3 presents the descriptive statistics of the indicators that were used in the analysis for high income countries.

Table 3. Descriptive Statistics of High income countries.

	EPFpc	EPRpc	CO2pc	GDPpc	Dens
Mean	0.004684	0.003144	10.39119	32,195.14	336.1680
Median	0.003691	0.000939	8.072146	27,729.19	109.5809
Maximum	0.021955	0.056814	67.31050	118,823.6	7952.998
Minimum	0.00000331	0	0.251345	1659.908	2.493134
Std. Dev.	0.004552	0.007736	8.274268	21,106.53	1028.928
Skewness	1.748568	4.755374	2.960003	1.164747	5.988748
Kurtosis	5.968018	28.28739	15.53083	4.738511	39.83826
Jarque-Bera	782.8296	27158.6	7146.537	314.3716	55,831.77
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000

The highest levels of electricity production from fossil fuels, throughout the studied time-period and among the 47 high income countries that were examined, were observed in Bahrain (0.021955 GWh/capita in 2006), while the lowest levels were observed in Uruguay (0.00000331 GWh/capita in 2003). Respectively, the highest levels regarding electricity production from renewable sources were observed in Iceland (0.0568 GWh/capita in 2015), while zero levels were observed in various countries throughout the studied time-period.

Qatar was the country with the highest levels of CO_2 emissions per capita for the whole time-period, with the highest being observed in 2001 (67.31 metric tons per capita); some of the lowest levels of CO_2 emissions per capita were observed in Malta and Uruguay. At the same time, in Luxembourg were observed the highest levels of GDP per capita, reaching $118,823.65 in 2014, while the lowest GDP per capita levels were observed in Romania ($1659.9 in 2000). The highest population density was observed in Singapore for the whole time-period (7952.998 people/sq.km in 2018), while the lowest population density was observed in Australia (2.49 people/sq.km in 2000).

Similarly, Table 4 presents the descriptive statistics for upper-middle income countries and Table 5 for lower-middle and low income countries. The highest levels of electricity production from fossil fuels, among the 33 upper-middle income countries were observed in Libya (0.005999 GWh/capita in 2013), while zero levels were observed in Paraguay and Albania for various years. Similarly, the highest levels of electricity production from renewable sources were observed in Paraguay (0.010049 GWh/capita in 2000), while zero levels were observed in Libya for the whole time period and in Botswana for the years 2000–2012.

Table 4. Descriptive Statistics of Upper-middle income countries.

	EPFpc	EPRpc	CO2pc	GDPpc	Dens
Mean	0.001757	0.000913	4.215383	5545.145	72.05436
Median	0.001421	0.000494	3.306489	4986.676	65.22279
Maximum	0.005999	0.010049	15.6463	19288.6	270.9931
Minimum	0	0	0.657959	622.7421	2.179756
Std. Dev.	0.001496	0.001577	3.090284	3226.249	58.80999
Skewness	0.751483	4.073107	1.262113	1.008053	1.092193
Kurtosis	2.593474	20.94012	4.227859	4.117945	4.357204
Jarque-Bera	63.3315	10141.95	205.8481	138.8408	172.7788
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000

Table 5. Descriptive Statistics of Lower-middle and Low income countries.

	EPFpc	EPRpc	CO2pc	GDPpc	Dens
Mean	0.000432	0.000232	1.139077	1470.063	134.9511
Median	0.000188	0.000133	0.611946	1133.186	73.57522
Maximum	0.002133	0.002499	15.1386	5591.212	1239.579
Minimum	0	0	0.01628	111.9272	1.543177
Std. Dev.	0.000575	0.000372	1.584955	1133.959	192.4295
Skewness	1.481985	4.07663	3.406818	1.232556	3.601976
Kurtosis	3.86273	22.02623	19.41762	3.9178	18.42611
Jarque-Bera	294.221	13229.1	9755.384	213.6282	8949.486
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000

The highest levels of CO_2 emissions were observed in Kazakhstan for the whole time period (15.65 metric tons per capita in 2011) and high levels were observed in the Russian Federation as well; the lowest levels of carbon dioxide emissions were observed in Paraguay for most of the studied years (0.658 metric tons per capita in 2005). Among the studied upper-middle income countries, Venezuela had the highest GDP per capita and Armenia had the lowest. Population density was higher in Jamaica for the whole studied time period (270.99 people/sq.km in 2018) and lower in Namibia for the whole time period (2.18 people/sq.km in 2000).

In the case of lower-middle & low income countries, the highest levels of electricity production from fossil fuels were observed in Ukraine (0.00213 GWh/capita in 2012), while zero levels were observed in Nepal, Ghana and the Republic of the Congo in various years. The highest levels of electricity production from renewable sources were observed in Tajikistan (0.0025 GWh/capita in 2005), while zero levels were observed in Niger, Mongolia and Benin for various years.

Mongolia presented the highest levels of CO_2 emissions for various years (15.14 metric tons per capita in 2013), while the Democratic Republic of the Congo presented the lowest levels for the whole time period (0.016 metric tons per capita in 2001). The highest GDP per capita was observed in Algeria ($5591.2 in 2012), while the lowest levels of GDP per capita were observed in Ethiopia ($111.93 in 2002). The highest levels of population density were observed in Bangladesh throughout the whole time period (1239.56 people/sq.km in 2018), while the lowest levels of population density were observed in Mongolia through the whole time period (1.54 people/sq.km in 2000).

By comparing the means, it can be observed that the highest levels of per capita electricity production from fossil fuels, as well as from renewable sources, were found in high income countries, while lower-middle & low income countries had significantly lower levels. The same can be concluded regarding CO_2 per capita levels: there are obvious differences in the levels of high income, upper-middle income and lower-middle & low income countries, with high income countries being those who pollute more. Population density was, on average, higher in high income countries and lower in upper-middle income countries.

5.2. Cross-Section Dependence and Unit Roots

Pesaran CD test is performed for each different data set, in order to test for cross-section dependence. The results reject the null hypothesis in all cases and suggest the existence of cross-section dependence (Table 6), indicating that unit root tests should be conducted. In addition, these results suggest the use of Driscoll-Kraay standard errors in the static regression models, in order to correct the variance-covariance matrix.

Table 6. Cross-section dependence (Pesaran CD test).

Variables	High Income	Upper-Middle Income	Lower-Middle & Low Income
EPFpc	23.065 *** [0.0000]	36.613 *** [0.0000]	31.038 *** [0.0000]
EPRpc	5.98 *** [0.0000]	6.94 *** [0.0000]	6.639 *** [0.0000]
CO2pc	40.812 *** [0.0000]	22.051 *** [0.0000]	54.969 *** [0.0000]
GDPpc	118.973 *** [0.0000]	85.592 *** [0.0000]	102.98 *** [0.0000]
Dens	46.212 *** [0.0000]	35.446 *** [0.0000]	94.99 *** [0.0000]

Note: The null hypothesis assumes that there exists no cross-section dependence (correlation). Significance at *** 1%.

Unit root tests are performed for each data set separately (Tables 7–9). The performed unit root tests (Fisher-ADF and Fisher PP) indicate that the examined variables are I(1) and evidence of stationarity exist in first differences.

Table 7. Fisher-ADF & Fisher-PP panel unit root test for high income countries.

Variables	Fisher—ADF	Fisher—PP		Fisher—ADF	Fisher—PP
Levels			*First Differences*		
EPFpc	55.3359 [0.9995]	66.67 [0.9853]	EPFpc	335.237 *** [0.0000]	871.135 *** [0.0000]
EPRpc	40.692 [1.0000]	705398 [0.8861]	EPRpc	308.303 *** [0.0000]	1128.62 *** [0.0000]
CO2pc	51.7633 [0.9999]	66.174 [0.9869]	CO2pc	336.321 *** [0.0000]	1207.49 *** [0.0000]
GDPpc	74.3357 [0.9331]	40.9579 [1.0000]	GDPpc	289.557 *** [0.0000]	389.16 *** [0.0000]
Dens	103.584 [0.2343]	79.5754 [0.8559]	Dens	232.967 *** [0.0000]	181.673 *** [0.0000]

Note: The null hypothesis assumes that the variable contains unit root. *P*-values in brackets. Significance at *** 1%.

Table 8. Fisher-ADF & Fisher-PP panel unit root test for upper-middle income countries.

Variables	Fisher—ADF	Fisher—PP		Fisher—ADF	Fisher—PP
Levels			*First Differences*		
EPFpc	46.8653 [0.9642]	66.8678 [0.4470]	EPFpc	257.191 *** [0.0000]	738.596 *** [0.0000]
EPRpc	23.9952 [1.0000]	28.9385 [1.0000]	EPRpc	273.322 *** [0.0000]	1072.02 *** [0.0000]
CO2pc	25.4143 [1.0000]	23.1849 [1.0000]	CO2pc	231.818 *** [0.0000]	743.485 *** [0.0000]
GDPpc	38.4883 [0.9973]	27.3549 [1.0000]	GDPpc	175.707 *** [0.0000]	273.061 *** [0.0000]
Dens	78.4815 [0.1397]	70.7227 [0.3230]	Dens	474.520 *** [0.0000]	229.837 *** [0.0000]

Note: The null hypothesis assumes that the variable contains unit root. *P*-values in brackets. Significance at *** 1%.

Table 9. Fisher-ADF & Fisher-PP panel unit root test for lower-middle & low income countries.

Variables	Fisher—ADF	Fisher—PP		Fisher—ADF	Fisher—PP
Levels			*First Differences*		
EPFpc	54.6241 [0.9796]	50.7312 [0.9929]	EPFpc	225.482 *** [0.0000]	674.029 *** [0.0000]
EPRpc	74.4705 [0.5923]	71.3106 [0.6907]	EPRpc	290.486 *** [0.0000]	1154.4 *** [0.0000]
CO2pc	47.9935 [0.9970]	54.6955 [0.9792]	CO2pc	275.946 *** [0.0000]	1002.39 *** [0.0000]
GDPpc	35.1546 [1.0000]	32.7017 [1.0000]	GDPpc	195.040 *** [0.0000]	546.373 *** [0.0000]
Dens	66.5735 [0.6584]	28.7294 [1.0000]	Dens	324.933 *** [0.0000]	124.692 *** [0.0006]

Note: The null hypothesis assumes that the variable contains unit root. *P*-values in brackets. Significance at *** 1%.

5.3. Cointegration

In order to test for panel cointegration, Westerlund panel cointegration tests are performed for each data set separately. The null hypothesis of no cointegration is rejected from the G_t and G_a statistics in almost every case, implying cointegration for at least one unit, as well as from the P_t and P_a statistics in almost every case, implying cointegration for the whole panel (Tables 10–12).

Table 10. Westerlund Panel Cointegration Test for high income countries.

Equation	Gt	Ga	Pt	Pa
CO2pc = f(GDPpc)	−5.665 *** [0.000]	−21.79 *** [0.000]	−30.947 *** [0.000]	−21.182 *** [0.000]
CO2pc = f(GDPpc^2)	−5.681 *** [0.000]	−24.376 *** [0.000]	−32 *** [0.000]	−21.387 *** [0.000]
CO2pc = f(GDPpc^3)	−5.742 *** [0.000]	−25.911 *** [0.000]	−33.582 *** [0.000]	−22.771 *** [0.000]
CO2pc = f(EPFpc)	−5.913 *** [0.000]	−21.832 *** [0.000]	−32.825 *** [0.000]	−17.976 *** [0.000]
CO2pc = f(EPRpc)	−5.335 *** [0.000]	−21.844 *** [0.000]	−35.717 *** [0.000]	−25.058 *** [0.000]
CO2pc = f(Dens)	−6.118 *** [0.000]	−12.374 [0.312]	−31.202 *** [0.000]	−9.953 [0.126]

Note: The null hypothesis assumes no cointegration. Significance at *** 1%.

Table 11. Westerlund Panel Cointegration Test for upper-middle income countries.

Equation	Gt	Ga	Pt	Pa
CO2pc = f(GDPpc)	−4.974 *** [0.000]	−18.636 *** [0.000]	−25.683 *** [0.000]	−17.946 *** [0.000]
CO2pc = f(GDPpc^2)	−5.047 *** [0.000]	−19.918 *** [0.000]	−24.775 *** [0.000]	−20.762 *** [0.000]
CO2pc = f(GDPpc^3)	−5.080 *** [0.000]	−21.058 *** [0.000]	−25.619 *** [0.000]	−21.604 *** [0.000]
CO2pc = f(EPFpc)	−5.165 *** [0.000]	−18.395 *** [0.000]	−26.173 *** [0.000]	−17.93 *** [0.000]
CO2pc = f(EPRpc)	−5.232 *** [0.000]	−19.344 *** [0.000]	−24.499 *** [0.000]	−22.053 *** [0.000]
CO2pc = f(Dens)	−6.119 *** [0.000]	−3.307 [0.998]	−20.493 *** [0.000]	−3.956 [0.999]

Note: The null hypothesis assumes no cointegration. Significance at *** 1%.

Table 12. Westerlund Panel Cointegration Test for lower-middle & low income countries.

Equation	Gt	Ga	Pt	Pa
CO2pc = f(GDPpc)	−4.896 *** [0.000]	−14.962 *** [0.002]	−28.97 *** [0.000]	−17.059 *** [0.000]
CO2pc = f(GDPpc^2)	−5.119 *** [0.000]	−15.827 *** [0.000]	−28.624 *** [0.000]	−18.073 *** [0.000]
CO2pc = f(GDPpc^3)	−5.129 *** [0.000]	−17.464 *** [0.000]	−28.318 *** [0.000]	−18.782 *** [0.000]
CO2pc = f(EPFpc)	−5.117 *** [0.000]	−17.313 *** [0.000]	−27.646 *** [0.000]	−17.906 *** [0.000]
CO2pc = f(EPRpc)	−4.493 *** [0.000]	−18.4 *** [0.000]	−26.339 *** [0.000]	−19.398 *** [0.000]
CO2pc = f(Dens)	−6.021 *** [0.000]	−2.731 [0.999]	−12.693 [0.710]	−3.51 [0.998]

Note: The null hypothesis assumes no cointegration. Significance at *** 1%.

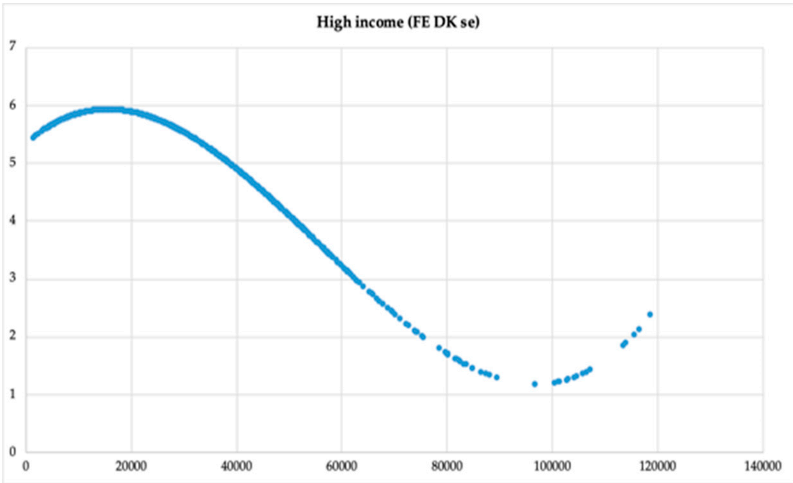
5.4. Regression Results

Six different regression models are constructed, in order to examine the existence of EKC curve and the relationships among the studied variables in different income levels. The Hausman tests imply the use of fixed effects model specifications and columns 2, 4 and 6 present the results of FE Driscoll-Kraay standard errors, as it was indicated by the Pesaran CD tests (Section 5.2).

The regression results for high income countries indicate that GDP per capita is a driver of CO_2 emissions per capita, by both Fixed Effects Method and GMM. An N-shaped curve is found to connect the studied variables in the static model, confirming the hypothesis that even higher income levels can increase environmental degradation. In the dynamic model, an inverted U-shape relationship is found to connect GDP per capita and CO_2 emissions per capita, supporting the existance of an inverted U-shaped curve and confirming the EKC hypothesis. The results for upper-middle income countries also confirm the EKC hypothesis, since an inverted U-shape curve is found to connect GDP per capita and CO_2 emissions per capita, in both static and dynamic models. In contrast, the EKC hypothesis is not confirmed in lower-middle & low income countries. The static model implies a positive monotonic relationship between GDP per capita and carbon dioxide emissions, while the dynamic model supports the existance of a U-shape relationship between the two variables. Figure 6 presents graphically these relationships between GDP per capita and CO_2 emissions for all three different income levels, in both static and dynamic models.

Electricity production from fossil fuels is found to be a significant driver of CO_2 emissions, in every model, both static and dynamic, and for each one of the three income levels. Electricity production from renewable sources is found to be linked with an inverse relationship with CO_2 emissions, in the dynamic model of high income countries and in both static and dynamic models of lower-middle and low income countries, while it is statistically insignificant in the models of upper-middle income countries. Population density is found to be linked with an inverse relationship with CO_2 emissions, in both static and dynamic model of upper-middle income countries, while it is a small driver in the dynamic models of high income and lower-middle and low income countries.

The lag of the dependent variables is an autoregressive-distributed lag specification that ends up to an AD (1,0) formulation, where insignificant variables dynamics aren't included. All variables are assumed to be strictly exogenous, except the lagged dependent. Lagged variables in the dynamic models have a value less than 1 and are statistically significant (1% level), indicating a strong conditional convergence.



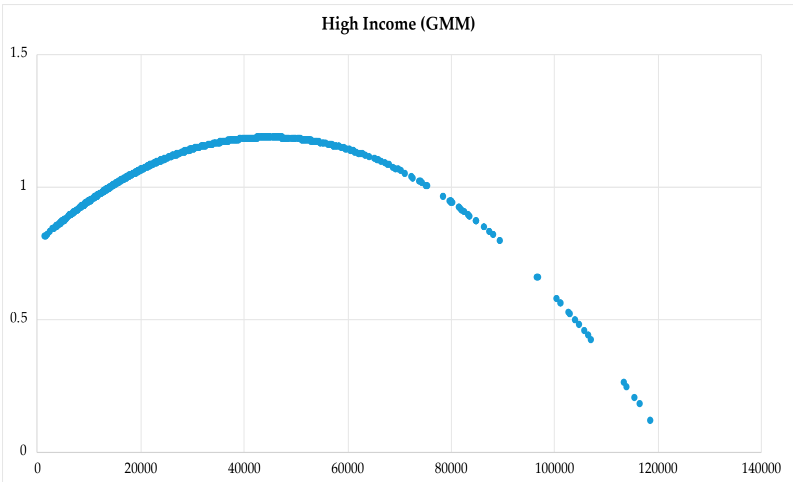
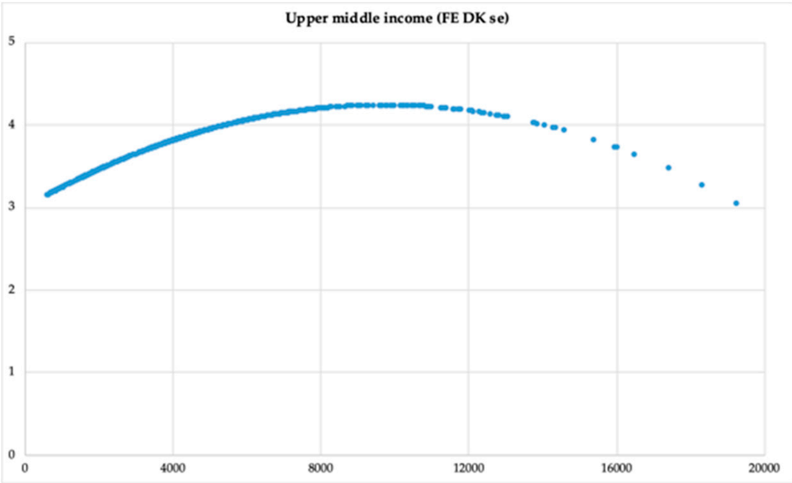
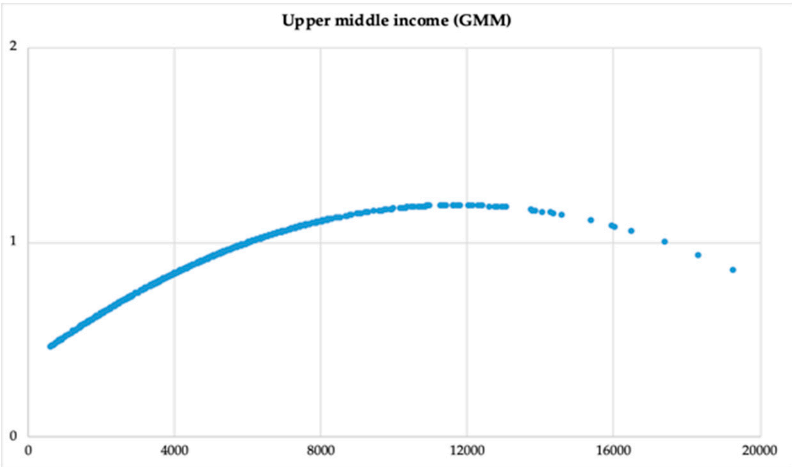


Figure 6. *Cont.*





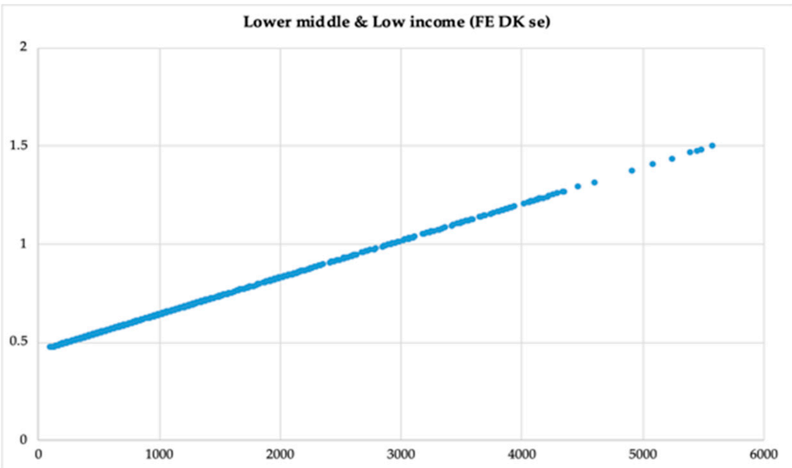


Figure 6. *Cont.*

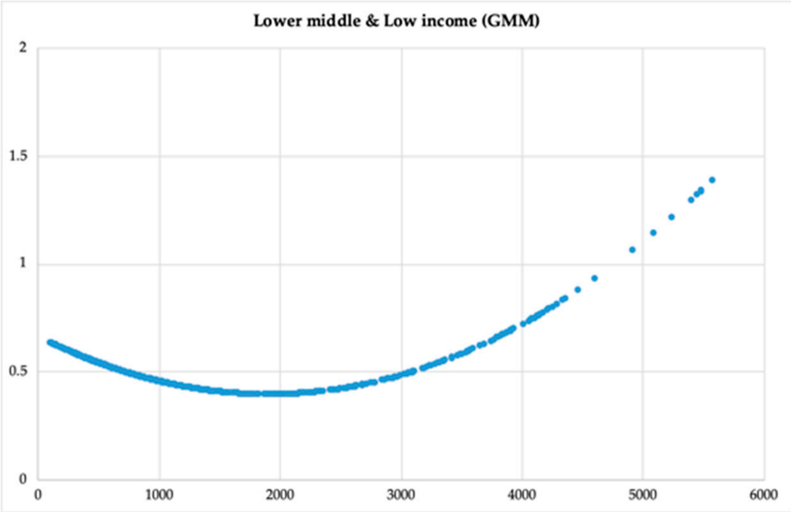


Figure 6. Derived relationships, where x axis represents GDP per capita and y axis CO_2 emissions per capita.

Since a lagged coefficient that equals 0 is an indication of instant adjustment, while a lagged coefficient that equals 1 is an indication of no adjustment [80], it is observed that the dynamic models of high income and lower-middle & low income countries present a slower adjustment to the equilibrium values, compared to the dynamic model of upper-middle income countries. More specifically, in the model of high income countries, the adjustment coefficient equals to 1–0.78. Since the lag coefficients show the adjustment to the equilibrium values, it can be seen that this adjustment equals to 22%, meaning that 22% of the discrepancy between actual and desired levels of efficiency is eliminated in a year; therefore, more than four periods are required for this adjustment. Similarly, the results of the lower-middle & low income countries model indicate that the adjustment coefficient equals to 1–0.67, meaning that 33% of the discrepancy between actual and desired levels is eliminated in a year and that approximately three periods will be required for this adjustment. In contrast, the dynamic model for upper-middle income countries presents an adjustment coefficient equal to 1–0.37, meaning that 63% of the discrepancy is eliminated in a year and that less than two periods will be required for the adjustment.

Both Wald tests of joint significance and Sargan tests of over-identifying restrictions are asymptotically distributed as χ^2 variables. Parentheses in Table 13 present the degrees of freedom. It can be seen that Sargan statistic does not reject the hypothesis of over-identifying restrictions and there is evidence of serially uncorrelated errors. AR(1) and AR(2) are first and second order serial autocorrelation tests, which indicate that the hypotheses of absence of autocorrelation is not rejected.

5.5. Granger Causality

In order to identify the relationships and the causality between the studied factors, Granger causality was examined for each one of the three datasets. Stacked test (with common coefficients) was chosen and 2 lags were included.

The results indicate that a bidirectional causality exists between GDP per capita and CO_2 emissions in all three different income levels, confirming the linkages that exist between these factors. A bidirectional causality is also found between GDP per capita and per capita electricity production from fossil fuels for high income and lower-middle & low income countries, while in the case of upper-middle income countries, a unidirectional causality is confirmed from electricity production from fossil fuels to GDP per capita.

Table 13. Regression results with CO2pc as dependent variable.

	High Income		Upper-Middle Income		Lower-Middle and Low Income	
	FE (DK se)	**GMM**	**FE (DK se)**	**GMM**	**FE (DK se)**	**GMM**
CO2(-1)		0.778178 *** (806.523)[0.0000]		0.373367 *** (28.541) [0.0000]		0.66676 *** (366.9915) [0.0000]
GDPpc	0.0000818 *** (4.17) [0.0001]	1.78E−05 *** (19.66458) [0.0000]	0.0002558 *** (12.39) [0.0000]	0.000138 *** (40.96653) [0.0000]	0.0001871 *** (2.91) [0.009]	−0.000283 *** (−72.10892) [0.0000]
GDPpc^2	−0.000000003 *** (−4.85) [0.000]	−0.000000000197 *** (−19.83668) [0.0000]	−0.0000000131 *** (−7.2) [0.0000]	−0.00000000587 *** (−18.86284) [0.0000]		0.0000000737 *** (77.43749) [0.0000]
GDPpc^3	0.0000000000000177 *** (3.99) [0.001]					
EPFpc	1144.766 *** (9.48) [0.000]	1277.639 *** (280.942) [0.0000]	947.1906 *** (10.09) [0.0000]	463.3203 *** (25.78434) [0.0000]	1664.963 *** (11.37) [0.000]	381.1654 *** (49.16397) [0.0000]
EPRpc		−451.2071 *** (−41.62376) [0.0000]			−669.3433 *** (−3.08) [0.006]	−153.8469 *** (−6.690689) [0.0000]
Dens		0.00427 *** (133.5502) [0.0000]	−0.0181993 *** (−8.08) [0.0000]	−0.018673 *** (−12.3941) [0.0000]		0.0000698 *** (3.230135) [0.0013]
within R^2	0.3105		0.5794		0.2478	
Hausman	13.56 *** [0.0011]		90.33 *** [0.0000]		4.79 * [0.0912]	
Wald test		598234.3 (5)		8420.45 (4)		35743.48 (5)
Sargan test		47.65923 (42)		28.71 (28)		31.4265 (33)
AR(1)		−2.285 ** [0.0223]		−2.362 ** [0.0182]		−2.288 ** [0.0221]
AR(2)		−0.7995 [0.4240]		−1.025 [0.3054]		−0.9359 [0.3493]
Shape of curve	N–shape	InvertedU–shape	Inverted U–shape	Inverted U–shape	Line	U–shape
Turning points	15859.25 56497.18	45177.67	9763.36	11754.69		1919.95
Observations	893	799	627	561	741	663

Note: t-Statistics in parentheses and *p*-values in square brackets. Parentheses in Wald and Sargan tests indicate degrees of freedom. Critical values for the Wald test of overall significance of the explanatory variables: $\chi^2_{0.05,5} = 11.07$, $\chi^2_{0.05,4} = 9.488$. Critical values for the Sargan test for over-identifying restrictions: $\chi^2_{0.05,42} = 58.124$, $\chi^2_{0.05,28} = 41.337$, $\chi^2_{0.05,33} = 47.4$. Significance at *** 1%, ** 5% and * 10%.

A unidirectional causality is also found from electricity production from fossil fuels to CO_2 emissions per capita, only for high income and lower-middle & low income countries, while this relationship is not confirmed in the case of upper-middle income countries. Instead, a causal relationship is found from CO_2 emissions to electricity production from fossil fuels for upper-middle income countries. In the case of high income countries, a bidirectional causality is found between GDP per capita and per capita electricity production from renewable sources, as well as between CO_2 emissions and population density. Electricity production from fossil fuels is found to Granger cause population density, in high income and lower-middle & low income countries. In lower-middle & low income countries, unidirectional causal relationships are also found from per capita electricity production from renewable sources to electricity production from fossil fuels and from population density to electricity production from renewables and to GDP per capita as well (Table 14).

Table 14. Granger Causality Results.

Null Hypothesis	High Income	Upper-Middle Income	Lower-Middle and Low Income
EPRpc does not Granger Cause *EPFpc*	0.1435 [0.8663]	0.84386 [0.4306]	8.49424 *** [0.0002]
EPFpc does not Granger Cause *EPRpc*	0.22982 [0.7947]	1.66069 [0.1909]	2.2018 [0.1114]
CO2pc does not Granger Cause *EPFpc*	1.14026 [0.3203]	5.78463 *** [0.0033]	1.68477 [0.1863]
EPFpc does not Granger Cause *CO2pc*	6.58308 *** [0.0015]	0.2931 [0.7461]	10.4235 *** [0.00003]
GDPpc does not Granger Cause *EPFpc*	9.3199 *** [0.0001]	0.78258 [0.4577]	4.17817 ** [0.0157]
EPFpc does not Granger Cause *GDPpc*	11.7925 *** [0.000009]	5.672 *** [0.0036]	5.40786 *** [0.0047]
Dens does not Granger Cause *EPFpc*	1.90495 [0.1495]	1.58869 [0.2051]	1.27445 [0.2803]
EPFpc does not Granger Cause *Dens*	7.17602 *** [0.0008]	0.51733 [0.5964]	4.85094 *** [0.0081]
CO2pc does not Granger Cause *EPRpc*	0.112 [0.8941]	0.90316 [0.4059]	0.5376 [0.5844]
EPRpc does not Granger Cause *CO2pc*	0.17197 [0.8420]	0.39549 [0.6735]	1.11302 [0.3292]
GDPpc does not Granger Cause *EPRpc*	4.5241 ** [0.0111]	0.85324 [0.4266]	0.29639 [0.7436]
EPRpc does not Granger Cause *GDPpc*	11.4263 *** [0.00001]	0.65071 [0.5221]	0.60933 [0.5440]
Dens does not Granger Cause *EPRpc*	0.00811 [0.9919]	2.22833 [0.1087]	2.52252 * [0.0810]
EPRpc does not Granger Cause *Dens*	0.0213 [0.9789]	0.43188 [0.6495]	0.0277 [0.9727]
GDPpc does not Granger Cause *CO2pc*	5.4029 *** [0.0047]	10.2292 *** [0.00004]	4.74665 *** [0.0090]
CO2pc does not Granger Cause *GDPpc*	3.1871 ** [0.0418]	19.8117 *** [0.000000005]	4.78144 *** [0.0087]
Dens does not Granger Cause *CO2pc*	13.151 *** [0.000002]	0.81525 [0.4431]	0.55917 [0.5720]
CO2pc does not Granger Cause *Dens*	3.64024 ** [0.0267]	0.26402 [0.7681]	1.38006 [0.2523]
Dens does not Granger Cause *GDPpc*	0.60785 [0.5448]	1.34882 [0.2604]	5.72788 *** [0.0034]
GDPpc does not Granger Cause *Dens*	1.38 [0.2522]	1.70387 [0.1829]	0.2997 [0.7411]
Observations	799	561	663

Note: t-Statistics in parentheses and *p*-values in square brackets. Rejection at *** 1%, ** 5% and * 10%.

6. Discussion

The present study confirms the existence of an inversed U-shaped curve for the 47 high income countries in the dynamic model and for the 33 upper-middle income countries in both static and dynamic quadratic model. These results suggest that environmental degradation increases along economic growth, but after a certain income level starts reducing. This indicates that, after reaching a certain level of growth, environmental measures and policies are promoted and there is a higher flow of resources towards environmental protection. At the same time, the results confirm the existence of an N-shaped curve in the static model of high income countries, confirming the assumption that, in high income countries, environmental degradation grows at first, as income grows, then starts reducing, after a certain income level, but it is once again increased at higher levels of GDP per capita [23]. Thus, it can be assumed that, in higher income levels, the existent measures and policies that had initially assisted in improving environmental conditions are not sufficient anymore, leading once more to an increase in environmental degradation. In the case of lower-middle and low income countries, the EKC hypothesis is not confirmed. The static model indicates a monotonic relationship where CO_2 emissions per capita increase as GDP per capita increases, while the dynamic model suggests the existence of a U-shape curve, meaning that in low income levels, GDP per capita has a negative effect on carbon dioxide emissions and it is only after a specific threshold ($1919.95 per capita) that higher GDP per capita increases CO_2 emissions and leads to environmental degradation. Thus, it can be seen that lower-middle & low income countries have to focus on other issues and on their growth and do not have the resources to invest in environmental protection.

The estimated turning points in the case of the static high income countries model, compared to the maximum GDP per capita observed in the studied period for the 47 high income countries, indicate that at least one country existed in the years 2000–2018 that had passed the second turning point and as GDP per capita increased, environmental degradation increased, too. The estimated turning point of the dynamic model for the high income countries indicates, compared to the same maximum GDP per capita, that there were countries that had passed this turning point as well and that they were in significantly higher GDP per capita levels. In the case of upper-middle income countries, the estimated turning points of both models indicate that there were countries that had passed the turning points and while their GDP per capita increased, their carbon dioxide emissions decreased. The estimated turning point of the dynamic lower-middle & low income countries model indicates that there were countries in the period 2000–2018 that had passed this turning point and their carbon dioxide emissions increased, as their GDP per capita increased.

Electricity production from fossil fuels is found to be a significant driver of CO_2 emissions in each one of the studied income levels, both in static and in dynamic models, confirming once again the negative environmental results that come with the use of fossil fuels. In addition, an inverse relationship exists between electricity production from renewable sources and carbon dioxide emissions, confirming thus the fact that higher percentages of electricity production covered from renewables can have a positive impact on the environment, reducing CO_2 emissions and, therefore, combating climate change.

Population density is linked with an inverse relationship with carbon dioxide emissions in the upper-middle income countries model, meaning that an increase in population density would lead to a decrease in CO_2 emissions. These results are also confirmed by various studies in the literature [81,82]. In contrast, the dynamic models of high income countries and lower-middle and low income countries suggest that population density is a small driver of CO_2 emissions.

This study also highlights the existence of a bidirectional Granger causality between GDP per capita and CO_2 emissions, while GDP per capita Granger causes per capita electricity production from fossil fuels in all income levels. This confirms the fact that the use of fossil fuels for electricity can indeed lead to economic growth while, at the same time, higher economic growth leads to a more intense use of fossil fuels in high income countries and lower-middle and low income levels. In addition, a unidirectional causality exists from per capita electricity production from fossil fuels to CO_2 emissions per capita in high income levels and lower-middle and low income levels, meaning that the use of fossil fuels leads to environmental degradation, while an increase in economic growth leads to an increase in air pollution. Per capita electricity production from renewable sources is found to Granger cause GDP per capita and, therefore, boost economic growth, only in high income countries, while in upper-middle and lower-middle & low income levels, this causality is not confirmed. This means that, in the period 2000–2018, the use of fossil fuels for electricity production in upper-middle and lower-middle and low income countries was necessary, in order to boost their economic growth.

The adjustment coefficients that were estimated in the GMM models indicate that 22% of the discrepancy between actual and desired levels is eliminated in a year in high income countries, 33% in lower-middle and low income countries and 63% in upper-middle income countries. It is obvious that the adjustment coefficients of the quadratic and the cubic model differ significantly. These results indicate that in low income levels, the adjustment of efficiency is relatively slow while, as income grows, the adjustment becomes faster. In higher income levels, the adjustment becomes slower again.

7. Conclusions and Policy Implications

The linkages between energy consumption, carbon dioxide emissions and economic growth have been extensively studied in the literature, as well as the causality existing among them. Especially in the case of environmental degradation and economic development, a variety of studies have been focusing on the Environmental Kuznets Curve hypothesis, which assumes that these two factors are linked with an inverse U-shaped relationship, while an N-shaped relationship is assumed to exist for high income countries.

This study aims to contribute to the existing literature, by examining the causal relationships that exist among carbon dioxide emissions, economic growth and electricity production from fossil fuels, as well as from renewable sources, for 119 world countries, classified based on their income levels, and for the years 2000–2018, while taking into consideration population density as well.

The results confirm the EKC hypothesis and the existence of an inverted U-shape curve in the dynamic model for high income countries and in both static and dynamic models for upper-middle income countries. The static model for high income countries confirms the N-shape curve, that is also confirmed in the literature, while the EKC hypothesis is not confirmed for lower-middle and low income countries. These results indicate that, lower-middle & low income countries do not have the resources required to invest in measures and policies related to environmental protection, since they have to focus on other issues regarding their development and growth. In contrast, upper-middle income countries, after reaching a certain level of growth, can promote measures and invest in environmental protection. The same is assumed for high income countries, according to the dynamic model; the static model for high income countries suggests that after a higher level of income, environmental degradation starts to increase again, indicating that all strategies and measures that were undertaken, were not sufficient for high growth levels.

These results can capture the situation existing in the world for the years 2000–2018, but the world has now entered a phase of energy transition, that includes changes in the electricity sector, where the use of renewables is more and more promoted [83]. This energy transition focuses on the use of new energy systems that are efficient and less harmful, but also has to take into consideration all the costs and risks related to the economy and the society that might result from such a transition and address them, so that this procedure will be sustainable [84].

The 13th Sustainable Development Goal, set by the United Nations in 2015, focuses on combating climate change, by promoting strategies and measures related to climate and by fostering resilience and adaptability. At the same time, the 8th SDG focuses on sustainable economic growth and on economic growth's disengagement from environmental degradation [85]; a relationship that was confirmed once again in this study. Even higher levels of GDP per capita are found to lead to higher levels of environmental degradation, but fossil fuels are considered to be essential, in order to cover current demand in electricity production. These results indicate that actions that minimize the exploitation of natural resources as well as the generation of pollutants and waste as GDP per capita grows and electricity demand is satisfied are necessary, in order to achieve the goals of sustainability.

In addition, the 7th SDG aims to reinsure that everyone in the world has access to reliable and sustainable energy sources, focusing on the reliance on clean fuels and on a higher share of renewables in world's final energy consumption [85]. The present study confirms once more the effects of fossil fuels on environmental degradation and the role of renewables on the improvement of environmental quality. At the same time, the study confirms the role of fossil fuels in boosting economic efficiency. These results highlight the urgent need for actions that promote energy transition and the targets of the 7th SDG, while taking into consideration all the necessary parameters, so that efficiency and growth are maintained.

In conclusion, the results of the present study, that highlight the relationships that existed among electricity production, economic growth and environmental degradation from the beginning of the 21st century, can be taken into consideration, along with the knowledge of new technologies, in order to fully understand those linkages in different income levels and undertake targeted actions that successfully promote energy transition, as well as the goals of sustainability. Different strategies should be implemented in countries of higher incomes, which have already achieved substantial socio-economic growth and have the necessary resources to invest in environmental protection and energy transition, while different measures should be implemented in lower-middle & low income countries, which have to focus mainly on their socio-economic development. Data shows that environmental degradation is caused primarily from higher incomes and the static model confirms that even higher income levels increase carbon dioxide emissions. Therefore, high income countries should focus on decreasing CO_2 emissions and on investing in environmental policies, while they should assist countries of lower incomes in their path of sustainable development, as should do countries of upper-middle income. In addition, and even though the EKC hypothesis is not confirmed for lower incomes and a positive relationship is found between economic growth and environmental degradation, it is suggested that lower-middle and low income countries should prioritize their socio-economic development, but without neglecting environmental protection, as the principles of sustainable development suggest.

Further analysis for specific countries is suggested, in order to identify with precision the linkages that exist between economic growth and carbon dioxide emissions in every place in the world separately, as well as more factors that have an impact on environmental degradation, while identifying the optimal shares of renewables and fossil fuels in electricity production. Such studies will be significantly important, in order to successfully promote energy transition with low socioeconomic costs and global sustainability.

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Article

The Nexus between Economic Growth, Energy Consumption, Agricultural Output, and CO_2 in Africa: Evidence from Frequency Domain Estimates

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Abstract: This study examined the nexus between economic growth, energy consumption, and the environment with the moderating role of agricultural value addition and forest in Africa based on data sourced from 1980 to 2019. We employed both the time domain and frequency domain panel Granger causality estimation techniques to compare results across the different horizons. Extant literature suggests the inability of time domain estimation techniques to account for causality at different frequencies. The study also accounts for the nexus among our variables both at the single-country and multi-country levels. The results at the single-country level are at best mixed. The results of the panel Granger causality at the frequencies domain suggest that a bi-directional relationship exists between energy consumption and economic growth, and that energy consumption Granger causes carbon emissions in Africa. The results align with the feedback hypothesis on the one hand but contradict the conservation hypothesis on the other hand. The study has some policy implications.

Keywords: energy consumption; carbon emissions; agricultural output; economic growth; Africa

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1. Introduction

In attaining sustainable development, energy, economics, and the environment play significant roles [1–5]. For instance, energy is crucial to the human economic and social development of any nation. It is estimated that global energy consumption will increase by about 56% from its current state in 2010 by the year 2040, as global aggregate demand is expected to double, given the expected increase in population [6–12]. However, the projected increase in total energy consumption is expected to be accompanied by an increase in carbon dioxide (CO_2) emissions, which is a core factor in total greenhouse emission (GHG). The energy sector is responsible for about 61.4% of the total global GHG [13–16]. Ref. [7] noted that the contributions of agriculture sector to the GHG are estimated to be between 14–30%, though evidence abounds to show that the agricultural sector possesses the ability to reduce GHG by 80–88%. It is opined that forests possess the capacity to accumulate atmospheric carbon after converting CO_2 into carbon and oxygen, and that about 430 tons of carbon per hectare is absorbed in the wet forest, hence, halting the effects of carbon emissions [17–22].

In the same vein, environmental degradation plays a crucial role in the continuous occurrence of natural disasters with unprecedented impacts on the economy. Disasters related to oil spillage, water pollution, solid waste management, deforestation, soil erosion, salinity and water, logging, and desertification, among others, affects the socio-economic wellbeing of a nation and increases climate change. Environmental degradation worsens with the exploitation of fossil fuels [23–27]. In order to mitigate this without losing a significant part of the energy output, economies over the years have opted for renewable energy sources [28–30]. Renewable energy offers clean and safer energy and can be derived from solar, tidal, wind, geothermal, hydro and biofuel power. Besides its alternative energy potential, it is useful in supporting employment, output, income, and job creation. Extant literature shows that the increase in economic growth and agricultural outputs have a positive impact on renewable energy [31,32]. Furthermore, given a global temperature increase of between 2–2.4 °C, renewable energy can help reduce carbon emissions by 50% by the year 2050. Besides its positive impact on the environment, renewable energy can reduce overdependency on foreign energy, given the fact that it is sourced domestically [33,34].

The United Nations Sustainable Development Goals (SDGs) emphasized the need to eradicate hunger (SDG 2), achieve clean energy utilization (SDG 7), achieve sustainable economic growth (SDG 8), adopt sustainable production and consumption (SDG 12), mitigate climate change through a sustainable clean environment (SDG 13), and adopt a global partnership model to achieve these goals (SDG 17). The nexus between these laudable metrics for sustainable development is key to exploring the linear and circular economic growth in any economy, be it regional or single country (Sarkodie 2020). Sub-Saharan Africa needs more energy than most continents of the world, given its ever-increasing, teaming population and quest for sustainable growth [35]. Even though the continent is endowed with an abundance of non-renewable energy like petroleum and other fossil fuels, the negative impacts of fossil fuel on the environment, such as the increase in GHG and other pollutants, calls for concerns. Although the contribution of Africa to global warming at present may be negligible compared with other continents, it is obvious that the continent will be disproportionately affected by its impact if nothing is done. To mitigate the impact of GHG on the continent, the African Development Bank (AfDB) adopted a ten-year green growth strategy (2013–2022) with an emphasis on developing the renewable energy potential capable of promoting resource efficiency and sustainable development.

Several theoretical models exist that explain the links between energy, the economy and the environment. For instance, Environmental Kuznets Curve (EKC) models suggest that at the initial stage of development, a direct positive relationship exists between economic growth proxy by real gross domestic product (RGDP) and environmental pollution, but the relationship becomes indirect after a threshold level of income is achieved. The pollution haven model suggests that in developing economies characterized by weak pollution protection laws, trade and investment liberalization laws often induce environmental degradation as pollution-intensive firms will find it easier to produce in such economies than in developed economies with stringent environmental protection policies. The causality model employs unit roots, cointegration and causality measures to examine the nexus between energy consumption and economic growth. This model offers four possibilities, firstly (i) the growth-led hypothesis, which suggests the existence of unidirectional causality from economic growth to energy consumption. This suggests that conservation policies will have no impact on economic growth. This is common in energy-sufficient economies. Secondly, (ii) the energy-led hypothesis, which suggests that energy consumption stimulates growth, therefore, energy conservation policies will impact negatively on economic growth, thus, energy expansion policies are required. This is common in economies that are energy-dependent like most developing economies. Third is (iii) the feedback model, which suggests the existence of a bi-directional causality between energy consumption and economic growth. The model suggest that both constructs are jointly determined and affected simultaneously. Lastly is (iv) the neutrality model, stating that no causality exists between energy consumption and economic growth. It also suggests that environmentally-friendly policies can be achieved without obstructing economic growth.

Extant literature has attempted to examine the link between the environment, energy, and the economy with mixed results. For instance, Refs. [36–38] were of the view that causality runs from economic growth to energy consumption while Refs. [39–43] opined that causality is from energy consumption to economic growth. Furthermore, Refs. [41,42,44,45] noted that causality runs from economic growth to CO_2 emissions. The bulk of these studies focused on developed economies with little attention on African economies. Africa is faced with plurality of issues, key among them being the need to stimulate growth, ensure a sustainable environment and reduce energy poverty. The World Bank global monitoring report (2008) highlights the need for the continent to be on a sustainable development path that embraces clean energy, a sustainable environment, and accelerated growth, noting the continuous increase in CO_2 emission and fall in per capita water resources. Given the low state of renewable energy development and the potential environmental hazards emanating from existing conventional fossil fuel amidst the desire to stimulate growth, it is imperative to examine the nature of the relationship between energy consumption (renewable and non-renewable), economic growth, and CO_2 emissions with the moderating impact of agriculture and agro-allied resources in Africa. Our study presents a short, intermediate, and long run analysis for 34 African economies. Unlike existing studies that employed time domain estimates like the traditional Granger causality estimates, VAR and other time domain estimates [16,30,46–49], the current study employed both the single and multi-country frequency domain Granger casualty estimates based on datasets sourced from 1980–2019. Even though frequency domain techniques offer better estimation models, because they allow for examination of the direction and level (strength) of the nexus at heterogeneous scales for frequency [2,3,9,50–52], they are yet to be explored especially in studies in Africa.

Our choice of Africa was induced by the fact that Africa is endowed with an abundance of potential energy resources (both renewable and non-renewable). It is estimated that in Africa, the potential energy generation capacity is up to 1.2 terawatts, excluding solar, and more than 10 terawatts including solar, with a high potential of achieving more than a 25% increase in clean energy by 2040 [8,53,54]. The continent is the world's youngest and fastest urbanizing continent, but it is the least energy-supplied, with annual consumption being 518 kwh in sub-Saharan Africa, equivalent to what a single member country of the OECD will use. Economic indices show that recently, African economies largely outperformed the global average (IMF, WB 2019) with the continent's overall GDP increasing 3.8% against the global average of 3.4%. Data availability large influences the choice of sample economies.

Against this background, this research attempts to know whether various energy policies in the continent offer the ability to end Africa's energy poverty, stimulate growth, and promote environmental sustainability. We intend to answer the following questions: (i) What drives the African economic, energy and environmental nexus—an environmental Kuznets curve, causality, or the pollution haven model? (ii) What is the nature of the causality between energy consumption (renewable and non-renewable) and economic growth, carbon emissions, and agricultural output in Africa? (iii) If causality is established, to what extent will the increase in energy consumption support economic growth, agricultural output, and reduce carbon emissions in Africa economies? Answering our questions will provide insights into at least five SDGs: SDG 2—zero hunger; SDG 7—achieve clean energy utilization; SDG 8—achieve sustainable economic growth; SDG 12—adopt sustainable production and consumption; and SDG 13—mitigate climate change through a sustainable clean environment.

This study will make essentially four contributions to the literature. First, in terms of methodology, we will provide a frequency-based panel Granger causality analysis that offers short, intermediate and long run casual estimates of the nexus between economic growth energy and the environment with a focus on African economies. Our method provides individual estimates for each of the economies studied, unlike the conventional methods that offer lump-sum causality estimates. Second, the study will calibrate the moderating impact of agriculture and agro-allied resources to the discourse on energy, economics and the environment in Africa. Africa is largely agrarian and to the best of the author's knowledge, no literature of the African extraction has considered the moderating role of agriculture in absorbing carbon emissions in the economic-energy-environmental nexus. Thirdly, in term of coverage and scope, our study will cover more African economies than most of the existing studies and use more recent data when compared with others. Fourthly, our study will also calibrate both the energy conservation and expansion policies into the energy, environment, and economic growth discourse. Our finding offers some policy implications for policy makers at both the national and regional levels, as well as for international organizations and researchers on the link between energy, economic and the environment. The rest of the study is as follows: Section 2 presents the literature review; Section 3 offers the data and methodology; Section 4 deals with the presentation of results, while Section 5 concludes the study and offers some policy implications.

2. Literature Review

A critical assessment of extent literature clearly suggests that frequency domain estimates are yet to be sufficiently employed in examining the nature of the relationship between energy, economics and the environment with the moderating role of agriculture, especially based on evidence from Africa, despite its attractiveness and potential strength in providing measures in shaping the African policy space. Africa economies are in dire need of energy, with the need to advance economic growth at the front of the policy framework amidst the global quest to reduce CO_2. It is pertinent, especially when faced with few publications on the subject matter, to examine the moderating role of agriculture in mitigating CO_2 emissions, stimulating economic growth and ending energy poverty. Such effort would not only offer a valuable platform to examine the nature of cointegration and the direction of causation, among the variables (energy, economics, environment and agriculture), it will equally initiate and stimulate further research and model specifications.

Table 1 presents the result of extent literature on the nexus between energy, economic growth, agriculture, and carbon emissions for a number of economies across the globe. The results as presented can be categorized into four main streams—methodological, results (findings), hypothesis or policy trust and variables employed. In methodological strands, a number of studies employed cointegration and/or Granger causality methods to investigate the link between energy, economic growth, and the environment [6,16,19,20,22,23,28,49,55–63] with mixed results. For instance, while [19] noted that a bi-directional relationship exists between non-renewable energy and climate change and that climate change Granger causes renewable energy for 16 African countries, ref. [16] observed that causation is from RGDP to renewable energy in the long run for China, with a negative impact on renewable energy in the short run. Similarly, ref. [13] documented the existence of a bi-directional relationship between renewable energy and non-renewable energy for India and South Africa, suggesting validity of the feedback hypothesis. The study further noted that causality runs from non-renewable energy to economic growth for Brazil and USA, an indication that the growth hypothesis is valid in these economies but noted no causal relationship exists between non-renewable energy and economic growth for Russia, India and South Africa, implying the validity of the neutrality hypothesis. For South Africa, ref. [6] noted that growth hypothesis is valid as the direction of causation is from energy use to RGDP. Ref. [19] offers multifaceted results, for instance, the authors documented that bi-directional relationships exist between fossil fuel and RGDP, between fossil fuel and CO_2, and between CO_2 and RGDP for the oil-exporting economies. These results support the feedback hypothesis from oil prices to each of RGDP and CO_2 for the oil-consuming economies, suggesting the validity of the growth hypothesis. Ref. [57] results are at variance with those of [22–24,28,29,58] who noted causality is from RGDP to CO_2, and that no causality exist between energy consumption and economic growth, thereby supporting the validity of the neutrality hypothesis in the studied economies.

Table 1. Summary of Literature review.

S/n	Authors	Period of Study	Variable	Methods	Countries	Results $\rightarrow\leftarrow$
1	[55]	1980–2014	Renewable energy, non-renewable, economic growth, climate change	Group-ARDL-PMG, ARDL-MG, Granger causality	16 African countries	Non-Renewable $\leftrightarrow$ Climate change Climate change $\rightarrow$ Renewable energy Feedback hypothesis holds.
2	[64]	1980–2019	Economic growth; CO_2 emission, inflation, population	Panel econometric methods of statistical analysis, Granger causality	6 west African countries	Positive relationship exists between the variables
3	[13]	1990–2013	GHG, fossil energy and economic growth	A recursive system of three equations	41 sub-Saharan African economies	Fossil energy $\rightarrow$ GHG, Economic growth does not Granger cause CO_2 emissions
4.	[65]	1996–2014	RGDP, non-renewable energy, CO_2, policy uncertainly	One-step-system GMM	32 sub-Sahara African countries	RGDP $\rightarrow$ CO_2 Non − renewable energy $\rightarrow$ CO_2 Policy uncertainty $\rightarrow$ CO_2 Renewable energy reduce $\rightarrow$ CO_2
5	[15]	2000–2015	RGDP, solid cooking fuels	Panel unit root, panel cointegration panel Granger causality	46 sub-Sahara African countries	A negative causal relationship exists from solid cooking fuel to RGDP
6.	[16]	1997–2017	Renewable energy, economic growth and financial development	Granger causality ARDL-PMG	China, Western China Eastern China	RGDP $\rightarrow$ RE (long run), financial development negatively impacts RE in the long run. RGDP negatively impacts RE in the short run; financial development positively impacts RE in of S/R
7	[17]	1990–2015	RGDP, NRE, RE, CO_2	System GMM	31 transitional economies	CO_2 has unconditional negative effects on human devt. RGDP; RGDP $\rightarrow$ RE, RE $\rightarrow$ CO_2N − RE $\rightarrow$ CO_2
8	[66]	1990–2018	Natural resources, energy consumption, gross capital formation, financial openness, RGDP	Structural equation modeling techniques	Pakistan	Negative relationship exists between natural resources and RGDP; RE and NRE $\rightarrow$ RGDP Fin. openness $\rightarrow$ RGDP. Gross capital formation $\leftrightarrow$ RGDP
9	[67]	1971–2014	Fossil oil RGDP	N-ARDL, asymmetric panel causality test	19 African countries	Mixed results
10	[14]	1971–2017	Electricity consumption, RGDP, agricultural output, govt. effectiveness trade	System GMM, advanced dynamic panel threshold regression model	17 African economies	Electricity $\rightarrow$ RGDP Growth hypothesis
11	[18]	1980–2015	Petroleum, natural gas, CO_2, RGDP	N-ARDL	Oil producing Africa economies	RE reduces CO_2 (Nigeria) RE $\rightarrow$ RGDP (Gabon) RE does not Granger cause CO_2 (Angola and Egypt). Growth and Neutrality hypotheses hold
12	[68]	1995–2014	Renewable energy labor, capital, RGDP	P-DOLS, F MOLS	15–Western Africa countries	RE slows down growth

Table 1. *Cont.*

S/n	Authors	Period of Study	Variable	Methods	Countries	Results →←
13	[56]	1996–2015	RE, NRE, R&D, RGDP	Unit root tests, panel Granger causality	BRICS	RE $\leftrightarrow$ NRE (India and SA) Feedback hypothesis hold RE does not granger cause NRE (Brazil) NRE $\rightarrow$ GDP (Brazil and SA) Growth hypothesis NRE–R&D (Russia, India, SA) Neutrality hypothesis hold
14	[6]	1960–2016	Capital, labor, CO_2, RGDP, energy consumption	ARDL, Granger causality test	South Africa	Energy use $\rightarrow$ RGDP growth hypothesis holds
15	[19]	1990–2015	Oil price, CO_2, RGDP, fossil energy consumption	PMG panel ARDL, bootstrap panel cointegration	22 African countries	Fossil $\leftrightarrow$ RGDP Fossil $\leftrightarrow$ CO_2 CO_2 $\rightarrow$ RGDP for non-oil exporter co_2RGDP $\leftrightarrow$ oil exporter Oil prices $\rightarrow$ RGDP, CO_2 and oil consumption for all
16	[25]	2001–2017	Energy consumption CO_2, RGDP	System GMM	68 developed, emerging and MENA countries	Energy consumption $\rightarrow$ RGDP Energy consumption $\rightarrow$ CO_2 CO_2 $\rightarrow$ RGDP in all countries except in MENA
17	[57]	1973–2014	Growth role of kg oil equivalent per capital energy usage, RGDP ecological foot print	ARDL Toda–Yamamoto	South Africa	Ecological footprint $\rightarrow$ RGDP Kg oil equivalent $\rightarrow$ eco. footprint Kg oil equivalent $\rightarrow$ RGDP
18	[69]	1990–2012	CO_2-equivalent, RGDP, energy usage, international trade	Environmental input-output model	Angola, Ethiopia, Kenya, Nigeria, south Africa	RE reduces CO_2-equivalent
19	[28]	1971–2010	Energy consumption CO_2, economic growth	ARDL, Granger causality	12 sub-Sahara Africa	Mixed results RGDP $\rightarrow$ CO_2 short run for Benin, DRC, Ghana, Nigeria, and Senegal RGDP $\leftrightarrow$ CO_2, Long run for Congo, Gabon Energy consumption $\rightarrow$ CO_2 in of long run for Benin, DRC, Nigeria, Senegal, South Africa, and Togo
20	[58]	1973–2017	Energy consumption, oil prices, trade openness, urbanization and RGDP	ARDL, ECM	African OPEC Countries	No causality between energy consumption and RGDP. Energy consumption does not Granger cause RGDP
21	[29]	1990–2017	RDGP, energy consumption, renewable energy	Neural network analysis	25 African economies	RGDP $\rightarrow$ CO_2
22	[6]	1990–2014	Energy intensity RE, CO_2, RGDP	ARDL, Toda Yamamoto	Romania	RE $\rightarrow$ RDGP, Energy intensity $\leftrightarrow$ RGDP
23	[20]	1975–2017	CO_2, RGDP, carbon income, trade openness, energy use	ARDL, Toda-Yamamoto	India	Energy use $\rightarrow$ GDP Energy use $\rightarrow$ CO_2
24	[59]	1980–2018	RE, CO_2, financial devt., trade openness, FDI, urbanization	A panel quantile regression	Global panel of 192 countries	Fin. devt $\rightarrow$ RE, inverse relationship exists between RE and CO_2
25	[21]	1990–2017	CO_2, trade, RGDP, RE, environmental innovation	A battery of panel co-integration methodologies	G7 countries	Long run relationship exists among CO_2, trade, RGDP, RE and environmental innovation. Environmental degradation does not cause RGDP, RE reduces CO_2

Table 1. *Cont.*

S/n	Authors	Period of Study	Variable	Methods	Countries	Results $\rightarrow\leftarrow$
26	[70]	1980–2014	CO_2, RGDP, RE, urbanization, NRE	FMOLS and GMM	28 sub-Sahara African Countries	NRE $\rightarrow$ CO_2 (S/R) NRE, RE $\rightarrow$ CO_2 (L/R) RGDP $\rightarrow$ CO_2
27	[22]	1978–2016	CO_2, RGDP, RE, urbanization and Agriculture	ARDL	Malaysia	RGDP, Urbanization $\rightarrow$ CO_2 RE and agriculture significantly CO_2
28	[23]	1990–2014	CO_2, RGDP, RE, nuclear energy real coal prices	Panel cointegration and Granger causality test	30 developed and emerging economies	LR relationship exists among the variables; NE does not lead to CO_2 reduction RE $\rightarrow$ CO_2 reduction RE $\rightarrow$ RGDP
29	[24]	2012–2014	Energy usage, CO_2, electricity consumption, fossil fuel, biomass	ANOVA and Tukey multiple comparison test	Sri Lanka	Elect $\rightarrow$ CO_2 Fossil $\rightarrow$ CO_2, RGDP does not $\rightarrow$ CO_2
30	[16]	1997–2017	RE, fin. devt and economic growth	ARDL-PMG Granger causality test	China	Economic growth $\rightarrow$ RE Negative relationship exists between fin. devt and RE
31	[30]	1995–2014	RE, CO_2, RGDP	GS2SLS	EU	EC $\leftrightarrow$ RE feedback ECC $\leftrightarrow$ CO_2 RE does not $\rightarrow$ CO_2
32	[46]	1990–2015	RE, NRE, RGDP	Local liner dummy variable estimation (LLDVE)	40 OECD and non-OECD countries	Both NRE and RE impact economic growth positively
33	[31]	1990–2017	RGDP, fin. inclusion, RE, NRE, CO_2, trade openness	Augmented mean group, Dumitrescu –Hurlin non-causality test	15 highest emitting countries	Bidirectional causality exists between fin. devt, economic growth, renewable energy utilization and ecological footprint; unidirectional causality runs from non-renewable energy and trade openness to ecological footprint, unidirectional relationship runs from economic growth to RE and trade openness. Feedback hypothesis holds
34	[32]	1990–2018	RE, RGDP, CO_2, NRE, Capital and labor	DOLS, FMOLS and Heterogeneous non-causality model	38 renewable energy consuming countries	LR relationship exist between RE and RGDP; RE, NRE, capital and labor impacts on RGDP
35	[71]	2005–2016	NRE intensity, urbanization, per capital income	Panel threshold regression	OECD countries	Positive and non-linear relationships exist between renewable energy and economic growth
36	[72]	1990–2010	GDP, GDPPC, Total renewable energy, share of renewable energy to total energy consumption, gross fixed capital formation, number of employed people in of economy; R&D	Panel quantile regression	OECD economies	The impact of RE on economic growth is at best unused, i.e., positive for lower, and low-middle–quantities, and negative for middle, high middle and higher quantities

Table 1. *Cont.*

S/n	Authors	Period of Study	Variable	Methods	Countries	Results →←
37	[73]	1991–2015	GDP and RE	Spatial Dublin model	26 European economies	Spatial dependences impact on the nexus between RE and GDP
38	[33]	1990–2014	CO_2, RE, EC	FMOLS and VECM	15 major RE consuming nations	EC ↔ RE for both S/R and LR supporting the feedback hypothesis; CO_2 does not cause RE in the LR, CO_2 ↔ RE in the SR, EC ↔ CO_2 both in the LR and SR
39	[60]	1990–2014	RE, pollution, EC, urbanization	Cointegration, Granger causality, impulse response function	Selected 106 countries	Both bidirectional and unidirectional relationship exists among the variables
40	[34]	1991–2014	RGDP, CO_2, technological innovation, trade and RE	Pedroni and Westerlund panel cointegration tests	Argentina, Brazil, Mexico, Colombia, Chile and Guatemala	Negative relationship exists between RE and CO_2 RGDP, technological innovation, and trade positively and significantly impact on RE production
41	[47]	1980–2017	Non-oil exports, tourism, RE and RGDP	ARDL, Johansen cointegration and Gregory –Hensen cointegration	Saudi Arabia	Non-oil export and tourism impact growth positively, long run cointegration exist between RE tourism, capital and RGDP
42	[61]	1960–2015	RE, RGDP, trade, urbanization, CO_2	ARDL, VECM Granger Causality tests	Australia and Canada	RGDP → CO_2 both in LR and SR for Australia; VECM results shows that RGDP, trade and RE → CO_2 in d LR and SR for Australia; for Canada, Trade → CO_2 for both LR and SR; RGDP, urbanization → CO_2 in of LR
43	[48]	1990–2014	RE, NRE, RGDP	Pedroni unit root tests, FMOLS, P-DOLS, Dumitrescue–Hurlin (2012)	5 South Asia countries	Positive impact of RE, NRE and fixed capital formation on growth RGDP → RE
44	[74]	1990–2014	Energy, efficiency, RE, RGDP	Fixed-effect panel quantity regression analysis	BRICS	Feedback hypothesis is valid RGDP ↔ EE RGDP ↔ RE EE → RE
45	[75]	1981–2016	Energy production, energy consumption, GDP	Hatemi –J cointegration, structural breaks, FMOLS, CCR VECM, Granger causality test	China	EP, EC → GDP, GDP → Gas consumption (supporting conservation hypothesis)
46	[49]	1971–2014	Ecological footprint, GDP, EC, GFCF	N-ARDL; asymmetric causality techniques	Pakistan	Environmental quality → EC neutrality hypothesis is valid among environmental quality, economic growth and capital

Table 1. *Cont.*

S/n	Authors	Period of Study	Variable	Methods	Countries	Results →←
47	[76]	2002–2011	CO_2, RE, NRE, RGDP	GMM and PMG	42	RE consumption leads to reduction in CO_2; RE has positive impact on RGDP; NRE has negative effect on RGDP in LR, substitute relationship exists between NRE and RE
48	[77]	1980–2015	NRE, GDP, human capital index, globalization, urbanization, added value of services	Threshold regression FEMOLS	27 developed OECD countries	Economic development does not reduce non-renewable energy consumption; Human capital development reduces NRE. LR relationship exist among globalization, urbanization, services and RE
49	[62]	1990–2015	Ecological footprint, per capital income, RE, life expectancy, population density	Cointegration tests, cross-sectional augmented autoregressive distributed lag	8 developing South and South-East Asian economies	The association between per capital income and ecological footprint is N-shaped, RE reduces ecological footprint, increase in population leads to increase in pollution emissions.
50	[54]	1992–2016	EC, financial development, urbanization, per capital GDP, gross domestic capital formation	A battery of static and dynamic econometric models	44 African economies	EC and fin devt, deteriorates the environment; urbanization impacts on the environment asymmetrically; per capital GDP has an asymmetric effect on the environment.
51	[63]	1995–2017	Total energy consumption RE, NRE, HCI, FD; eco-innovation, energy intensity, GDP, gross fixed capital formation R&D	Westerlund and Edgerton panel cointegration and augmented mean group	G7 countries	Negative relationship exists among HCI, eco-innovation, energy price, R&D and TEC, NREC. Positive relationship exists between financial development, and each of TEC and NREC. HCI, eco-innovation, energy price, R&D enhances REC. Financial development reduces REC
52	[8]	1990–2014	Energy efficiency RE, CO_2, NE	Panel quantity regression (PQR)	66 developing economies	EE reduces carbon emissions across all quantities. RE reduces CO_2 with substantial effect at 10th quartile. GDP increases CO_2
53	[78]	1980–2016	CO_2, RE, HCI, globalization, trade openness	ARDL	China	RE does not impact on CO_2, HCI reduces environmental degradation; globalization, trade openness, and income impact on pollution
54	[63]	1965Q1–2017Q4	EC, ecological footprint, NRE economic complexity	QARDL quantile Granger causality test	USA	Economic complexity and fossil fuel energy consumption significantly enhance ecological footprint; causality exist among economic complexity, energy consumption and ecological footprint
55	[36]	1990–2016	RE, RGDP	Bootstrap panel causality test	17 Emerging economies	Neutrality hypothesis holds for all the economies except Poland (no causality from either of the variables) RE → RGDP for Poland
56	[79]	1998–2018	RE, financial development, CO_2, Innovation RGDP	P-ARDL Dumitrescu–Hurlin Panel causality test	ASEAN + 3 group	Financial development → RE CO_2 and economic freedom has negative impact on RE positive relationship exist between innovation, RGDP and RE
57	[80]	1965Q1–2017Q4	RE, NRE, RGDP ecological footprint	QARDL Granger causality	Turkey	RE decreases ecological footprint in of LR; NRE and RGDP positively impact ecological footprint
58	[81]	1991–2012	RE, RGDP, institutions, CO_2	System-GMM FMOLS	85 developed and developing countries	RE positively impacts RGDP RE negatively impacts CO_2 institution positively impacts RGDP; institution negatively affect CO_2

Table 1. *Cont.*

S/n	Authors	Period of Study	Variable	Methods	Countries	Results →←
59	[82]	1990–2015	RE, NE, CO_2, RGDP, financial development	CIPS, FMOLS, bootstrap cointegration	74 countries	NRE has positive impact on CO_2. RE has negative impact on CO_2. Financial development has negative impact on CO_2
60	[83]	1980–2014	TE, RE, NRE, RGDP	NARDL	G7 countries	Asymmetric relationship exists between TE and RGDP
61	[22]	1978–2016	CO_2, RGDP, RE, urbanization, agriculture	ARDL	Malaysia	CO_2 is not directly influenced by modernization. Calibrating RE to agricultural sec tor will help in achieving sustainable agriculture and mitigate CO_2 emissions; CO_2 significantly decrease due to RGDP and urbanization

Note: ARDL, NARDL, GMM, FMOLS, DOLS, VECM, ARDL-PMG are autoregressive distributed lag, nonlinear autoregressive distributed lag, general moment method, vector error correction model, error correction model, fully modified ordinary least square, dynamic ordinary least square, autoregressive distributed lag model based on pooled mean group estimation, respectively.

The second strand of literature employs nonlinear models like quantile regression, system frequency domain estimate PMG, threshold regression, bootstrap estimates, NARDC, and recursive to examine the nature of relationship between energy, economic growth and CO_2 emissions with mixed results. For instance, [8,13,18,36,49,63,71,72,77,79,80,83] employed different versions of nonlinear models to examine the nexus between energy, economic growth, and CO_2 emissions with different results. Ref. [13] noted that fossil energy causes GHG, and that economic growth does not cause CO_2 emissions for 41 sub-Sahara African economies. Ref. [18] results from N-ARAL observed mixed findings; for example, the study noted that renewable energy reduces CO_2 emission for Nigeria, but no causality was documented between renewable energy and CO_2 for Angola and Egypt. The study further noted that renewable energy causes economic growth for Gabon, suggesting the validity growth hypothesis. Ref. [84] employed panel threshold for some selected OECD economies and reported the existence of positive and non-linear relationships between renewable energy and economic growth, an indication that the growth hypothesis holds. Ref. [49] employed the N-ARAL model and noted that environmental quality causes economic growth and that the neutrality hypothesis is valid, based on the results from environmental quality and capital stock. In a related development, [8] employed panel quantile regression to examine the nature of the relationship between energy, economic growth, and CO_2 for some selected 66 developing economies and noted that renewable energy reduces CO_2 with substantial effect at the 10th quantile, and that GDP increases CO_2. Ref. [63] results, based on quantity ARDL, suggest the validity of the feedback hypothesis among economic complexity, energy consumption and the ecological footprint. For emerging economies [36] employed a bootstrap panel causality test and noted that the neutrality hypothesis is valid for all the economies except Poland, whose results suggest that causality is from renewable energy to economic growth. The single country (Turkey) estimates from [80] analysis shows that renewable energy reduces the ecological footprint in the long run; surprisingly, the results documented that non-renewable energy and economic growth positively impact on the ecological footprint.

3. Materials and Methods

This study examined the nature of the relationship between CO_2 emissions, energy consumption, agriculture and economic growth for some selected [34] Africa economies. Though Africa is made up of 54 independent countries, the selection of countries is largely influenced by data availability. The collected data cover the period 1980–2019. This period and the countries covered allow for examination of convergence issues inherent in the literature with adequate geographical covering of the African continent. The variables employed are annual data of GDP per capita (constants are 2010 and USD); CO_2 emissions per capita (metric tons); EC representing energy consumption; agriculture proxy by agricultural value added (AVA) per capita contribution of agriculture to GDP; and forest area (forest area as percentage of total land mass). The variables are expressed in natural forms such that $InCO_2$, $In\gamma$, $InEC$, $InAVA$; $InFoR$ represent carbon emissions, economic growth, energy consumption, agricultural value chain and forest area, respectively. The data for the study are sourced as follows: CO_2 and RGDP from World Development Indicators (various issues), agriculture value addition and forest areas from Food and Agricultural Organization (various issues), and energy consumption data were from the OECD.

Methodology

As stated earlier, the study employed a frequency domain analysis to examine the relationship among energy, economic growth, and carbon emissions with the moderating impact of agriculture. Our preference of frequency domain estimates over time domain techniques is largely influenced by the weakness noticed in time domain estimates. For instance, time domain estimates cannot examine causality at different frequencies as they can only calculate a single test statistic over time [85–87]. Further, if the nexus among the variables is connected to more than one frequency, the ability of time dimension estimate to explore the information from the original data set becomes ineffective [88,89]. To overcome this, Geweke (1982) developed the Wald test procedure that employed linear constraints on coefficient parameters to test Granger causality in a certain frequency range. This procedure was extended by [90,91] as single country frequency domain causality test [85]. The [91] single country frequency domain causality test was further extended to a multi-country model by [92]. This extended frequency domain (panel Granger causality test) allows us to determine if the predictive power is concentrated at quick or slow fluctuating components. The current study aims at examine the nexus between the variables using both single-country and multi-country causality tests by following [85,93–95]. The tests are thus presented.

Single-Country Causality Test:

We begin our single country causality test by following [2] Gorus and Aydin 2019 specification of the [90] single test procedure stated as follows:

$$X_t = \sum_{j=1}^{p}\theta_{11.j}X_{t-j}+\sum_{j=1}^{p}\theta_{12.j}Y_{t-j}+\varepsilon_{1t} \tag{1}$$

Here, θ_{11} and θ_{12}, are the coefficients of the polynomials, ε_{1t} represents the error term, p represent the lag length, the constraint is on the first VAR, we express the constraints on the null hypothesis of "no Granger causality from Y_t to X_t at the frequency w" as stated below:

$$\sum_{j=1}^{p}\theta_{12.j}cos(jw) = 0,$$

$$\sum_{j=1}^{p}\theta_{12.j}sin(jw) = 0. \tag{2}$$

To test these constraints, we employed the incremental R^2 measurement test, calculated as follows:

$$R_I^2 = R^2 - R_*^2 \tag{3}$$

Here, R^2 and R_*^2 are derived from the unrestricted and restricted models, respectively. (**) The null hypothesis is rejected if this condition is observed:

$$R_I^2 > F_{(2T-2p,\ 1-\propto)}\ \frac{2}{T-2p}\left(1-R^2\right) \tag{4}$$

Multi-Country Causality Test:

Following [92], the study employed the seemingly unrelated regression (SVR) model stated as follows:

$$X_{i,t} = \sum_{j=1}^{p}\beta_{i,j}X_{i,t-j} + \sum_{j=1}^{p}\gamma_{i,j}Y_{i,t-j} + \varepsilon_{i,t},\ i=1,\ 2,\ 3,\ \ldots,\ N. \tag{5}$$

Here, $X_{i,t}$ and $Y_{i,t}$ are the variables of country i at time t, p is the lag length, N represent the number of countries and $\varepsilon_{i,t}$ represents the error term at time t of country i. The null hypothesis constraints are expressed as follows:

$$\sum_{j=1}^{p}\gamma_{i.j}cos(jw) = 0,\ i = 1,\ 2,\ 3,\ \ldots,\ N$$

$$\sum_{j=1}^{p}\gamma_{i,j}sin(jw) = 0,\ 1,\ 2,\ 3,\ \ldots,\ N. \tag{6}$$

We tested these constraints using the incremented R^2 measured test, expressed as follows:

$$R_I^2 = R^2 - R_*^2 \tag{7}$$

Here, R^2 represent the unrestricted and R^2_* represents the restricted McElroy R^2 value expressed as follows:

$$R_I^2 > F_{(2N,\, N(T-2P),\, 1-\propto)} \frac{2N}{N(T-2p)} \left(1 - R^2\right) \tag{8}$$

We rejected the null hypothesis of no Granger causality from Y_t to X_t at the frequency 'w' in the studied countries if Equation (8) was observed.

4. Results

The descriptive statistics and normality results of the variables employed in this study are presented in Table 2. The results suggested that the value of the Jarque-Bera statistics was greater than 5% for the variables, suggesting validity of normality in each of the variables studied.

Table 2. Descriptive statistics of the variables.

Variables	Descriptive Analysis				Normality Analysis (Natural Log-Form)			
	Mean	Max.	Min.	SD	Skewness	Kurtosis	Jarque-Bera	Probability
$In\gamma$	175.98	298.77	142.67	39.09	−0.78	2.44	4.97	0.07
$InEC$	63.18	28.07	32.62	32.12	−0.48	2.14	4.22	0.06
$InAVA$	158.78	197.09	102.11	28.09	−0.55	3.09	498	0.08
$InCO_2$	1.97	2.41	1.66	0.31	0.17	1.55	3.21	0.22
$InFOR$	2.99	4.01	1.98	0.55	0.05	1.61	2.76	0.22

Source: Authors' computations 2022.

The results of both the cross-section dependency (CD) tests and the panel unit root tests are presented in Table 3. We began our analysis by investigating the cross-section dependency (CD) of the series, followed by conducting a check on the stationary properties of the series using the panel unit root test. The result in Table 3 suggest that cross-sectional dependency exists among the variables. This implies that shocks in any of the economies study can affect any of the rest. Having established cross-sectional dependency, we employed the cross-sectional augmented Dickey-Fuller test developed by [96], which is effective in detecting stationary properties of panel data as used in the current study [85,94,95]. The results suggests that $In\gamma$ and $InAVA$ are stationary at the first different I(1), and that $InEC$, $InCO_2$, and $InFOR$ are stationary at their level value I(0).

Table 3. Cross-section dependence and panel unit root tests for the series.

Variables	CD_{BP}	CD_{LM}	CD	CIPS Statistics
$In\gamma$	457.899 ***	76.558 ***	3.234 ***	−0.988
$InEC$	417.219 ***	51.521 ***	3.004 ***	−0.918
$InAVA$	398.881 ***	47.908 ***	9.176 ***	−2.955 **
$InCO_2$	366.098 ***	56.897 ***	8.077 ***	−2.344 **
$InFOR$	564.092 ***	41.179 ***	12.098 ***	−3.756 **
$\Delta In\gamma$	-	-	-	−3.665 ***

Note: *** and ** suggest the rejection of the null hypothesis at 1% and 5% significance level, respectively. CIPS Statistics provides the simple average of the individual CADF statistics ($\overline{CADF_i}$).

5. Discussion

Frequency Domain Results

As earlier stated, the study intends to examine the nature of relationship among energy, economic growth, carbon emissions, forests, and agricultural added value at three (3) clear frequencies: short, intermediate and long run denoted as 2.5, 1.5 and 0.5, respectively. Results in the long run (0.5) implies that a permanent causality exists while the results in the short run (2.5) suggest temporary causality exists. In Tables 4–10, we present the results of the frequency domain causality based on single-country estimates. Table 4 presents the results of the link between economic growth and CO_2 emission for each of the 34 African economies. The results as presented suggest that a unidirectional (at the three spectra) causality runs from economic growth to CO_2 emission for Algeria, Angola, Benin, Burkina Faso, Ghana, Kenya, Morocco, Nigeria, Senegal, South Africa, and Zambia. The findings are in line with [13,29,61], but contradict [17,18,67] The results further reveals that a one-way causality both at the intermediate and long run is noted to exist from emission to economic growth for Congo, Madagascar, Mali, Rwanda and Zimbabwe. The results from the rest of the economies studied suggest that no link can be established between CO_2 and economic growth. This finding supports the validity of the neutralization hypothesis in these economies; thus, emission curbing policies can be applied in these economies. The results from Algeria, Angola, Benin, Burkina Faso, Ghana, Kenya, Morocco, Nigeria, Senegal, South Africa, and Zambia suggest that environmental protection laws could be harmful to the economy.

In Table 5, we present the results of the link between energy consumption and economic growth for the selected African economies. The results suggest that a bi-directional relationship exist between the two for the economies of Algeria, Ghana, Kenya, Morocco, and Nigeria (at the three periods), South Africa (at intermediate and long run), Egypt (at the short run and intermediate), and at least one for each of Cameroon, Guinea, and Madagascar. These results support the validity of the feedback hypothesis in these economies. The results further reveal that an un-directional causality runs from economic growth to energy consumption for the economies of Mozambique, Namibia, Tanzania and Uganda in the short run, this suggests that the conservation hypothesis is rational in these economies. The growth hypothesis is validated based on the existence of causality from economic growth to energy consumption for the economies of Algeria, Ghana, Kenya, Morocco and Nigeria. The results are in line with the findings of [30,33,74].

Table 6 presents the results of the nexus between energy consumption and CO_2 emissions in the studied economies. The results reveal that energy consumption Granger causes carbon emissions in Nigeria, Algeria, Egypt, Tunisia and Ghana, suggesting that the pollution haven hypothesis is valid for these economies at short, intermediate and long runs. The results support the findings of [65] but disagree with [55].

The results of the causality between economic growth and agricultural value addition, as presented in Table 7, suggest that bi-directional causality is noted for almost all the studied economies at the short, intermediate, and long runs. The result is not surprising because agriculture constitutes the bulk of African GDP.

Table 8 shows that for most the studied economies, a unidirectional relationship runs from forestry to economic growth; this suggests that wood sourced from the forest support economic growth in the studied economies.

In Table 9, we present the results of the relationship between energy consumption and agricultural value addition across the three spectra of our analysis. The results reveal that there is a unidirectional causality from energy consumption to agricultural value addition in Egypt, Ghana, Tunisia and Uganda, whereas a bi-directional causality is documented for the economies of Nigeria, South Africa, Angola. This suggests that the feedback hypothesis is validated based on the relationship between energy consumption and agriculture in these economies. The results of the relationship between forestry and energy consumption are almost the same with those of agriculture and energy consumption, except that a one-way causality is noted to exist between forestry and energy consumption, suggesting the validity of the conservative hypothesis in these economies.

Table 10 we present the results of causality between CO_2 emission and agricultural value addition for the selected Africa economies. Our results reveal that no causality exists between these variables for the economies studies.

Table 4. Granger causality tests in the frequency domain estimates ($In\gamma,\ InCO_2$).

Panel A								
Countries	**H$_0$: $In\gamma \nrightarrow InCO_2$**				**H$_0$: $InCO_2 \nrightarrow In\gamma$**			
	w = 0.5	**w = 1.5**	**w = 2.5**	**c.v. = 10%**	**w = 0.5**	**w = 1.5**	**w = 2.5**	**c.v. = 10%**
Algeria	0.013 ***	0.055 ***	0.128 ***	0.111	0.023	0.027	0.034	0.111
Angola	0.017 ***	0.005 ***	0.005 ***	0.009	0.034	0.036	0.044	0.113
Burkina Faso	0.096 ***	0006 ***	0.001 ***	0.009	0.023	0.027	0.054	0.112
Benin	0.073 ***	0.054 ***	0.022 ***	0.072	0.026	0.028	0.034	0.114
Cameron	0.091	0.071	0.004	0.014	0.019	0.016	0.045	0.116
Congo (Brazzaville)	0.009	0.002	0.005	0.012	0.029	0.019	0.034	0.112
Congo (DRC)	0.047 ***	0.008 ***	0.006	0.009	0.03 *	0.021 **	0.045	0.111
Egypt	0.004 ***	0.044 ***	0.007 ***	0.008	0.023	0.028	0.054	0.112
Ethiopia	0.021	0.046	0.017	0.065	0.033	0.038	0.048	0.118
Gabon	0.009	0.032	0.014	0.008	0.035	0.037	0.039	0.112
Ghana	0.019 ***	0.044 ***	0.011 ***	0.011	0.045	0.054	0.037	0.114
Guinea	0.009	0.008	0.012	0.116	0.037	0.031	0.038	0.132
Kenya	0.022 ***	0.045 ***	0.011 ***	0.113	0.039	0.032	0.045	0.161
Lesotho	0.031	0.032	0.012	0.114	0.029	0.024	0.055	0.115
Madagascar	0.011 ***	0.017 ***	0.014	0.111	0.018 **	0.021 **	0.034	0.113
Malawi	0.032	0.019	0.001	0.102	0.024	0.027	0.049	0.112
Mali	0.022 ***	0.039 ***	0.009	0.019	0.032	0.036	0.054	0.122
Mauritius	0.005	0.033	0.004	0.112	0.036	0.037	0.032	0.141
Morocco	0.007 ***	0.032 ***	0.007 ***	0.133	0.029	0.031	0.035	0.112
Mozambique	0.046	0.037	0.006	0.121	0.017	0.021	0.041	0.116
Namibia	0.033	0.081	0.009	0.114	0.029	0.037	0.039	0.114
Nigeria	0.044 ***	0.033 ***	0.014 ***	0.111	0.025	0.028	0.057	0.123
Rwanda	0.006 ***	0.023 ***	0.012	0.112	0.044 **	0.034 **	0.045	0.114
Sao Tome and Principe	0.045	0.012	0.009	0.115	0.031	0.028	0.055	0.152
Senegal	0.044 ***	0.008 ***	0.006 ***	0.117	0.022	0.026	0.055	0.143
Sierra Leone	0.032	0.091	0.008	0.111	0.019	0.021	0.053	0.122
South Africa	0.031	0.023	0.005	0.112	0.022 *	0.026 *	0.058 *	0.144
Tanzania	0.029	0.033	0.006	0.111	0.027	0.029	0.059	0.115
Togo	0.031	0.034	0.009	0.122	0.032	0.035	0.077	0.122
Tunisia	0.033	0.023	0.008	0.111	0.028	0.031	0.056	0.127
Uganda	0.045	0.031	0.006	0.121	0.029	0.031	0.055	0.157
Zambia	0.033	0.022	0.009	0.111	0.019	0.022	0.054	0.138
Zimbabwe	0.046	0.036	0.045	0.123	0.021	0.023*	0.067*	0.136

***, **, * represent 1%, 5%, 10% significant levels, respectively.

Table 5. Granger causality tests in the frequency domain estimates $In\gamma$, $InEC$.

Countries	H$_0$: $In\gamma \nrightarrow InEC$				H$_0$: $InEC \nrightarrow In\gamma$			
	w = 0.5	**w = 1.5**	**w = 2.5**	**c.v. = 10%**	**w = 0.5**	**w = 1.5**	**w = 2.5**	**c.v. = 10%**
Algeria	0.023 ***	0.031 ***	0.022 ***	0.012	0.031 ***	0.029 ***	0.027 ***	0.111
Angola	0.001	0.004	0.003	0.002	0.041 ***	0.037 ***	0.034 ***	0.112
Burkina Faso	0.007	0.012	0.011	0.005	0.029	0.044	0.027	0.099
Benin	0.012	0.014	0.019	0.006	0.031	0.039	0.027	0.122
Cameron	0.018	0.019 *	0.012	0.009	0.014	0.037 *	0.034	0.117
Congo (Brazzaville)	0.021	0.016	0.014	0.021	0.016	0.039	0.029	0.112
Congo (DRC)	0.064	0.044	0.032	0.017	0.018	0.068	0.029	0.110
Egypt	0.017	0.022 ***	0.026 ***	0.005	0.031	0.039 ***	0.033 ***	0.117
Ethiopia	0.024	0.022	0.033	0.006	0.042	0.054	0.039 ***	0.102
Gabon	0.021 ***	0.019 ***	0.017 ***	0.011	0.033	0.056	0.027	0.115
Ghana	0.031 ***	0.021 ***	0.019 ***	0.013	0.067 ***	0.011 ***	0.034 ***	0.111
Guinea	0.026	0.024 *	0.021	0.004	0.028	0.032 *	0.045	0.115
Kenya	0.021 ***	0.019 ***	0.017 ***	0.021	0.028 ***	0.034 ***	0.054 ***	0.119
Lesotho	0.016	0.019	0.022	0.024	0.021	0.044	0.048	0.167
Madagascar	0.017	0.021 *	0.025	0.031	0.027	0.045 *	0.039 ***	0.109
Malawi	0.014	0.017	0.022	0.024	0.029	0.056	0.037	0.114
Mali	0.022	0.025	0.029	0.001	0.41	0.059	0.038	0.112
Mauritius	0.019	0.015	0.011	0.005	0.039	0.041	0.045	0.109
Morocco	0.021 ***	0.022 ***	0.023 ***	0.017	0.033 ***	0.039 ***	0.055 ***	0.112
Mozambique	0.022	0.021	0.029	0.013	0.028	0.034 **	0.034	0.119
Namibia	0.031	0.023	0.034	0.014	0.032	0.041 **	0.049	0.166
Nigeria	0.027 ***	0.028 ***	0.029 ***	0.011	0.031 ***	0.044 ***	0.054 ***	0.112
Rwanda	0.003	0.031	0.022	0.009	0.027	0.033	0.032	0.114
Sao Tome and Principe	0.009	0.010	0.013	0.002	0.025	0.029	0.035	0.141
Senegal	0.023 ***	0.025 ***	0.027 ***	0.003	0.029	0.049	0.041	0.117
Sierra Leone	0.031	0.041	0.034	0.008	0.023	0.044	0.039	0.118
South Africa	0.052 ***	0.024 ***	0.027	0.003	0.028	0.046 ***	0.057 ***	0.114
Tanzania	0.023	0.022	0.027	0.011	0.031	0.041 **	0.045	0.119
Togo	0.054	0.042	0.034	0.014	0.038	0.038	0.055	0.109
Tunisia	0.037 ***	0.031 ***	0.029 ***	0.011	0.037	0.039	0.045	0.115
Uganda	0.044	0.032	0.029	0.023	0.033 ***	0.031 ***	0.054 ***	0.167
Zambia	0.022	0.031	0.033	0.015	0.028	0.033	0.048	0.117
Zimbabwe	0.023	0.034	0.039	0.014	0.024	0.032	0.039	0.115

***, **, * represent 1%, 5%, 10% significant levels, respectively.

Table 6. Granger causality tests in the frequency domain estimates $InEC,\ InCO_2$.

Countries	H_0: $InEC \nrightarrow InCO_2$				H_0: $InCO_2 \nrightarrow InEC$			
	w = 0.5	w = 1.5	w = 2.5	c.v. = 10%	w = 0.5	w = 1.5	w = 2.5	c.v. = 10%
Algeria	0.023 ***	0.027 ***	0.031 ***	0.091	0.029 ***	0.028 ***	0.034 ***	0.032
Angola	0.034	0.036	0.041	0.007	0.023 ***	0.031 ***	0.044 ***	0.014
Burkina Faso	0.023	0.027	0.029	0.012	0.028	0.010	0.054	0.006
Benin	0.026	0.028	0.031	0.014	0.031	0.025	0.034	0.044
Cameron	0.019 **	0.016 **	0.014 **	0.017	0.038 ***	0.041 ***	0.045 ***	0.009
Congo (Brazzaville)	0.029	0.019	0.016	0.019	0.037	0.024	0.034	0.018
Congo (DRC)	0.037	0.021	0.018	0.081	0.033	0.022	0.045	0.092
Egypt	0.023 ***	0.028 ***	0.031 ***	0.089	0.028	0.042	0.054	0.078
Ethiopia	0.033	0.038	0.042	0.091	0.024	0.031	0.048	0.099
Gabon	0.035	0.037	0.033	0.071	0.029	0.032	0.039	0.077
Ghana	0.045 ***	0.054 ***	0.067 ***	0.009	0.023	0.031	0.037	0.101
Guinea	0.037	0.031	0.028	0.008	0.028	0.034	0.038	0.111
Kenya	0.039	0.032	0.028	0.045	0.029	0.028	0.045	0.098
Lesotho	0.029	0.024	0.021	0.076	0.018	0.031	0.055	0.102
Madagascar	0.018	0.021	0.027	0.089	0.024	0.010	0.034	0.111
Malawi	0.024	0.027	0.029	0.090	0.032	0.025	0.049	0.133
Mali	0.032	0.036	0.41	0.039	0.036	0.041	0.054	0.122
Mauritius	0.036	0.037	0.039	0.051	0.029	0.024	0.032	0.121
Morocco	0.029	0.031	0.033	0.044	0.017	0.022	0.035	0.090
Mozambique	0.017	0.021	0.028	0.062	0.029	0.042	0.041	0.112
Namibia	0.029	0.037	0.032	0.082	0.025	0.031	0.039	0.122
Nigeria	0.025 ***	0.028 ***	0.031 ***	0.095	0.044	0.032	0.057	0.124
Rwanda	0.044	0.034	0.027	0.083	0.031	0.031	0.045	0.154
Sao Tome and Principe	0.031	0.028	0.025	0.076	0.029	0.034	0.055	0.101
Senegal	0.022	0.026	0.029	0.049	0.018	0.028	0.055	0.111
Sierra Leone	0.019	0.021	0.023	0.078	0.024	0.031	0.053	0.121
South Africa	0.022	0.026	0.028	0.065	0.024	0.010	0.058	0.132
Tanzania	0.027	0.029	0.031	0.007	0.032	0.025	0.059	0.122
Togo	0.032	0.035	0.038	0.009	0.036	0.041	0.077	0.176
Tunisia	0.028 ***	0.031 ***	0.037 ***	0.065	0.029 **	0.024 **	0.056 **	0.109
Uganda	0.029	0.031	0.033	0.098	0.017 **	0.022 **	0.055 **	0.101
Zambia	0.019	0.022	0.028	0.097	0.029	0.042	0.054	0.102
Zimbabwe	0.021	0.023	0.024	0.008	0.025	0.031	0.067	0.111

***, **, represent 1%, 5% significant levels, respectively.

Table 7. Granger causality tests in the frequency domain estimates $In\gamma,\ InAVA$.

Countries	H_0: $In\gamma \nrightarrow InAVA$				H_0: $InAVA \nrightarrow In\gamma$			
	w = 0.5	w = 1.5	w = 2.5	c.v. = 10%	w = 0.5	w = 1.5	w = 2.5	c.v. = 10%
Algeria	0.029 ***	0.031 ***	0.034 ***	0.023	0.014 ***	0.045 ***	0.035 ***	0.019
Angola	0.038 ***	0.042 ***	0.045 ***	0.009	0.015 ***	0.015 ***	0.045 ***	0.098
Burkina Faso	0.034 **	0.044 **	0.047 *	0.008	0.093 *	0008 **	0.053 **	0.116
Benin	0.022 **	0.026 *	0.029 ***	0.012	0.072 **	0.053 **	0.034 *	0.122
Cameron	0.023 *	0.027 **	0.029 *	0.019	0.093 *	0.072 **	0.047 **	0.138
Congo (Brazzaville)	0.021 **	0.026 **	0.029 **	0.076	0.007 **	0.009 *	0.034 ***	0.129
Congo (DRC)	0.022 **	0.025 **	0.028 *	0.027	0.043 *	0.005 **	0.045 *	0.147
Egypt	0.019 **	0.023 **	0.029 **	0.098	0.007 **	0.042 **	0.053 **	0.126
Ethiopia	0.018 *	0.022 **	0.027 **	0.056	0.027 ***	0.041 **	0.047 **	0.091
Gabon	0.016 **	0.019 **	0.022 **	0.039	0.005 **	0.033 **	0.041 **	0.125
Ghana	0.022 *	0.025 **	0.029 ***	0.044	0.015 **	0.042 **	0.037 *	0.087
Guinea	0.018 **	0.021 **	0.027 *	0.087	0.005 *	0.006 **	0.034 ***	0.099
Kenya	0.007 ***	0.012 **	0.019 ***	0.069	0.027 *	0.046 ***	0.053 **	0.102
Lesotho	0.018 **	0.011 **	0.019 **	0.081	0.038 **	0.036 **	0.059 **	0.009
Madagascar	0.019 **	0.022 **	0.026 **	0.072	0.016 *	0.016 *	0.039 *	0.122
Malawi	0.022 *	0.023 **	0.026 **	0.098	0.036 *	0.016 *	0.047 **	0.134
Mali	0.027 *	0.029 *	0.031 *	0.099	0.026 *	0.036 **	0.054 *	0.177
Mauritius	0.032 *	0.028 *	0.024 *	0.062	0.009 **	0.038 *	0.045 **	0.187
Morocco	0.009 *	0.014 *	0.019 **	0.073	0.009 *	0.037 **	0.065 **	0.138
Mozambique	0.007 **	0.009 *	0.011 **	0.079	0.047 *	0.034 **	0.044 ***	0.166
Namibia	0.009 ***	0.012 **	0.019 ***	0.092	0.037 **	0.083 **	0.098 *	0.147
Nigeria	0.011 ***	0.014 *	0.019 **	0.095	0.047 ***	0.034 **	0.059 **	0.123
Rwanda	0.021 **	0.025 **	0.028 *	0.093	0.009 *	0.024 **	0.043 **	0.122
Sao Tome and Principe	0.012 *	0.018 *	0.022 **	0.091	0.047 **	0.015 **	0.058 ***	0.111
Senegal	0.024 **	0.027 *	0.032 ***	0.084	0.049 **	0.005**	0.058 *	0.145
Sierra Leone	0.022 **	0.026 ***	0.029 *	0.079	0.039 **	0.094 *	0.054 **	0.118
South Africa	0.011 *	0.016 *	0.019 **	0.099	0.039 **	0.025 **	0.056 **	0.128
Tanzania	0.022 **	0.026 *	0.028 **	0.078	0.041 **	0.035 **	0.055 *	0.101
Togo	0.021 **	0.025 **	0.029 *	0.055	0.033 **	0.035 *	0.074 *	0.109
Tunisia	0.009 **	0.011 *	0.016 **	0.089	0.034 *	0.025 **	0.053 **	0.154
Uganda	0.019 *	0.023 **	0.029 **	0.037	0.047 *	0.035 **	0.055 *	0.111
Zambia	0.021 *	0.026 *	0.031 *	0.088	0.037 *	0.025 **	0.055 *	0.122
Zimbabwe	0.007 *	0.011 **	0.019 *	0.089	0.043 **	0.035 **	0.064 **	0.143

***, **, * represent 1%, 5%, 10% significant levels, respectively.

Table 8. Granger causality tests in the frequency domain estimates $In\gamma,\ InFOR$.

Countries	H_0: $In\gamma \nrightarrow InFOR$				H_0: $InFOR \nrightarrow In\gamma$			
	w = 0.5	w = 1.5	w = 2.5	c.v. = 10%	w = 0.5	w = 1.5	w = 2.5	c.v. = 10%
Algeria	0.009	0.011 *	0.019	0.091	0.005	0.033	0.044	0.093
Angola	0.004	0.012 *	0.019	0.009	0.009	0.005	0.048	0.098
Burkina Faso	0.011 *	0.015	0.019	0.017	0007	0.023	0.056	0.099
Benin	0.003	0.009	0.011	0.019	0.005	0.024	0.037	0.092
Cameron	0.005 ***	0.009 ***	0.012 ***	0.089	0.001	0.029	0.048	0.091
Congo (Brazzaville)	0.002 ***	0.006 ***	0.009 ***	0.079	0.002	0.036	0.037	0.078
Congo (DRC)	0.003 ***	0.007 ***	0.022 ***	0.097	0.008	0.034	0.049	0.103
Egypt	0.006	0.009 *	0.011	0.087	0.004	0.032	0.057	0.099
Ethiopia	0.011	0.017 *	0.021	0.057	0.006	0.032	0.056	0.094
Gabon	0.008	0.012 *	0.022	0.023	0.002	0.039	0.044	0.109
Ghana	0.007	0.014 *	0.021	0.028	0.004	0.041	0.039	0.111
Guinea	0.003	0.008 *	0.011	0.055	0.008	0.034	0.040	0.104
Kenya	0.008 ***	0.013 ***	0.019 ***	0.089	0.005 *	0.039 **	0.047 *	0.101
Lesotho	0.009	0.022 **	0.029	0.082	0.002	0.039	0.058	0.099
Madagascar	0.014	0.023 *	0.029	0.044	0.007	0.031	0.038	0.102
Malawi	0.021	0.022 **	0.028	0.043	0.009	0.037	0.056	0.101
Mali	0.008	0.044 *	0.054	0.049	0.009	0.045	0.057	0.078
Mauritius	0.014	0.021 *	0.034	0.076	0.003	0.045	0.055	0.099
Morocco	0.022	0.025 *	0.029	0.077	0.002	0.042	0.053	0.089
Mozambique	0.028	0.031 *	0.045 *	0.073	0.007	0.031	0.045	0.098
Namibia	0.027	0.031 *	0.048 *	0.071	0.001	0.043	0.048	0.067
Nigeria	0.021 ***	0.027 ***	0.037 ***	0.082	0.003	0.048	0.057	0.089
Rwanda	0.011	0.033	0.054	0.091	0.003	0.041	0.045	0.098
Sao Tome and Principe	0.023 *	0.043	0.055	0.027	0.002	0.020	0.054	0.044
Senegal	0.011 ***	0.033 ***	0.058	0.031	0.008	0.035	0.053	0.056
Sierra Leone	0.012	0.027	0.039	0.036	0.001	0.051	0.054	0.019
South Africa	0.009 ***	0.014 ***	0.051 ***	0.042	0.003	0.034	0.052	0.110
Tanzania	0.019	0.026	0.031	0.043	0.003	0.032	0.053	0.101
Togo	0.008	0.015	0.029	0.055	0.004	0.052	0.071	0.089
Tunisia	0.007	0.017	0.032	0.069	0.003	0.041	0.052	0.091
Uganda	0.009 ***	0.032 ***	0.054 ***	0.072	0.001	0.042	0.052	0.088
Zambia	0.011	0.028	0.038	0.058	0.002	0.041	0.052	0.078
Zimbabwe	0.013	0.029	0.054	0.098	0.006	0.044	0.062	0.098

***, **, * represent 1%, 5%, 10% significant levels, respectively.

Table 9. Granger causality tests in the frequency domain estimates $InEC$, $InAVA$.

Countries	H_0: $InEC \nrightarrow InAVA$				H_0: $InAVA \nrightarrow InEC$			
	w = 0.5	w = 1.5	w = 2.5	c.v. = 10%	w = 0.5	w = 1.5	w = 2.5	c.v. = 10%
Algeria	0.009	0.014	0.029	0.121	0.024	0.029	0.033	0.101
Angola	0.011 ***	0.026 ***	0.037 ***	0.019	0.024	0.032	0.042	0.103
Burkina Faso	0.008	0.039	0.044	0.019	0.024	0.012	0.052	0.102
Benin	0.029	0.044	0.039	0.082	0.034	0.023	0.032	0.104
Cameron	0.011	0.029	0.037	0.024	0.034	0.043	0.041	0.106
Congo (Brazzaville)	0.028	0.031	0.039	0.032	0.034	0.022	0.031	0.102
Congo (DRC)	0.027	0.058	0.068	0.019	0.035	0.023	0.041	0.101
Egypt	0.013 ***	0.025 ***	0.039 ***	0.018	0.025	0.043	0.052	0.102
Ethiopia	0.029	0.033	0.054	0.095	0.025	0.032	0.044	0.108
Gabon	0.011	0.023	0.056	0.008	0.024	0.033	0.035	0.102
Ghana	0.013 ***	0.028 ***	0.011 ***	0.101	0.025	0.033	0.034	0.104
Guinea	0.016	0.022	0.032	0.016	0.025	0.035	0.034	0.102
Kenya	0.012	0.024	0.034	0.013	0.024	0.024	0.043	0.101
Lesotho	0.014	0.026	0.044	0.104	0.019	0.035	0.053	0.105
Madagascar	0.011	0.033	0.045	0.101	0.023	0.014	0.033	0.103
Malawi	0.009	0.045	0.056	0.101	0.033	0.024	0.042	0.102
Mali	0.006	0.054	0.059	0.009	0.032	0.045	0.051	0.102
Mauritius	0.008	0.023	0.041	0.102	0.021	0.025	0.037	0.101
Morocco	0.007	0.033	0.039	0.103	0.019	0.024	0.034	0.102
Mozambique	0.004	0.021	0.034	0.101	0.022	0.044	0.043	0.106
Namibia	0.006	0.025	0.041	0.104	0.023	0.034	0.033	0.104
Nigeria	0.009 ***	0.029 ***	0.044 ***	0.101	0.041 ***	0.033 ***	0.054 ***	0.103
Rwanda	0.012	0.028	0.033	0.102	0.034	0.036	0.043	0.104
Sao Tome and Principe	0.009	0.026	0.029	0.105	0.019	0.033	0.052	0.112
Senegal	0.007	0.028	0.049	0.107	0.019	0.023	0.057	0.103
Sierra Leone	0.006	0.039	0.044	0.101	0.021	0.034	0.056	0.102
South Africa	0.005 ***	0.028 ***	0.046 ***	0.114	0.022 ***	0.014 ***	0.054 ***	0.104
Tanzania	0.017	0.021	0.041	0.113	0.033	0.023	0.053	0.195
Togo	0.022	0.029	0.038	0.124	0.031	0.043	0.073	0.102
Tunisia	0.017 ***	0.022 ***	0.039 ***	0.112	0.021	0.023	0.053	0.107
Uganda	0.018 ***	0.023 ***	0.031 ***	0.123	0.019	0.024	0.053	0.107
Zambia	0.012	0.028	0.033	0.112	0.019	0.041	0.052	0.108
Zimbabwe	0.014	0.029	0.032	0.124	0.021	0.032	0.062	0.119

*** represent 10% significant level.

Table 10. Granger causality tests in the frequency domain estimates $InCO_2$, $InAVA$.

Panel G								
Countries	**H_0: $InCO_2 \nrightarrow$, $InAVA$**				**H_0: $InAVA \nrightarrow InCO_2$**			
	w = 0.5	**w = 1.5**	**w = 2.5**	**c.v. = 10%**	**w = 0.5**	**w = 1.5**	**w = 2.5**	**c.v. = 10%**
Algeria	0.006	0.023	0.034	0.019	0.013	0.032	0.049	0.114
Angola	0.005	0.033	0.044	0.027	0.017	0.052	0.059	0.115
Burkina Faso	0.002	0.032	0.054	0.025	0.096	0.043	0.069	0.118
Benin	0.009	0.029	0.034	0.025	0.073	0.056	0.061	0.117
Cameron	0.011	0.023	0.045	0.023	0.091	0.058	0.062	0.111
Congo (Brazzaville)	0.012	0.029	0.034	0.021	0.009	0.055	0.069	0.124
Congo (DRC)	0.021	0.032	0.045	0.089	0.047	0.055	0.062	0.101
Egypt	0.024	0.044	0.054	0.099	0.004	0.058	0.061	0.102
Ethiopia	0.022	0.033	0.048	0.094	0.021	0.074	0.051	0.108
Gabon	0.012	0.022	0.039	0.072	0.009	0.054	0.052	0.123
Ghana	0.009	0.029	0.037	0.011	0.019	0.054	0.051	0.124
Guinea	0.019	0.029	0.038	0.011	0.009	0.054	0.061	0.102
Kenya	0.015	0.028	0.045	0.056	0.022	0.066	0.069	0.101
Lesotho	0.013	0.039	0.055	0.076	0.031	0.037	0.049	0.112
Madagascar	0.021	0.029	0.034	0.019	0.011	0.052	0.059	0.117
Malawi	0.025	0.023	0.049	0.091	0.032	0.044	0.058	0.115
Mali	0.005	0.032	0.054	0.071	0.022	0.055	0.064	0.102
Mauritius	0.014	0.024	0.032	0.080	0.005	0.051	0.054	0.101
Morocco	0.011	0.028	0.035	0.049	0.007	0.051	0.069	0.102
Mozambique	0.012	0.013	0.041	0.069	0.046	0.051	0.052	0.119
Namibia	0.018	0.029	0.039	0.089	0.033	0.051	0.058	0.119
Nigeria	0.022	0.041	0.057	0.099	0.044	0.071	0.072	0.129
Rwanda	0.021	0.032	0.045	0.089	0.006	0.051	0.064	0.117
Sao Tome and Principe	0.012	0.039	0.055	0.072	0.045	0.056	0.065	0.155
Senegal	0.022	0.033	0.055	0.091	0.044	0.056	0.058	0.141
Sierra Leone	0.014	0.023	0.053	0.071	0.032	0.067	0.069	0.128
South Africa	0.022	0.034	0.058	0.069	0.031	0.034	0.071	0.148
Tanzania	0.008	0.023	0.059	0.009	0.029	0.055	0.071	0.112
Togo	0.006	0.032	0.077	0.011	0.031	0.044	0.059	0.121
Tunisia	0.008	0.029	0.056	0.066	0.033	0.055	0.062	0.121
Uganda	0.009	0.022	0.055	0.093	0.045	0.053	0.064	0.150
Zambia	0.019	0.021	0.054	0.091	0.033	0.056	0.068	0.132
Zimbabwe	0.021	0.029	0.067	0.009	0.046	0.056	0.064	0.131

The results of the panel Granger causality in the frequency domain for all the examined African economies suggest the existence of bi-directional relationships across the three spectra between economic growth and energy consumption. The results further reveal that a one-way Granger causality runs from energy consumption to CO_2 emission in the studied economies. A further examination of the results also suggests that there is a causal nexus between carbon emissions and economic growth for the entire spectra studied, and that no evidence suggests that causality runs from economic growth to carbon emissions. In term of theoretical underpinning, one can deduce that the feedback hypothesis is valid for the relationship between energy consumption and economic growth in the studied African economies. This suggests that African economies could grow their economies by increasing energy consumption, and that energy consumption could also be enhanced by growing the economy, suggesting that demand for energy consumption is a booster of economic growth. For the nexus between energy consumption and CO_2 emission, the results suggest the validity of the pollution haven hypothesis, as energy consumption has a bi-directional relationship with growth driving carbon emissions in African economies, thus, Africa economies, while pursuing growth, should start looking at clean energy consumption. Though the results of the study suggest that no causality runs from economic growth to carbon emissions, ruling out the possibility of the pollution haven hypothesis, the existence of causality from energy consumption to carbon emissions points to the existence or potential of the pollution haven hypothesis, which could be from an indirect perspective. On the meditating role of agricultural value addition and forests, the results noted that the impact of both forests and agricultural value addition is only significant on economic growth across all the spectra, and on energy consumption in the short run. No causality is established between either of forests and agricultural value addition, and CO_2 emission for the studied economies.

For comparison, we conducted time domain estimates for the entire region by employing the Dumitrescu–Hurlin panel causality estimate. From the results, it could be deduced that a bi-directional relationship exists between economic growth and energy consumption, and that a one-way causality runs from energy consumption to carbon emissions. The results suggest the feedback hypothesis is valid on the nexus between energy and economic growth in Africa. The results of the one-way nexus, however, suggest that the conservation hypothesis is not valid in Africa. Unlike the frequency domain estimate, the moderating variables failed exhibit any form of causality in the time domain model.

The study has made some significant contribution to knowledge by being among the first set of studies that has examined the nexus among energy, environment and economic growth in Africa within the context of frequency domain estimate, and that calibrated the moderating roles of forest and agricultural value addition to this nexus.

6. Conclusions

The essence of this study was to examined the causal relationships between energy consumption, economic growth and CO_2 emission with the moderating roles of forestry and agricultural value addition in Africa, by employing both time domain and frequency domain estimates to analyzed data sourced from 1980 to 2019. The study provides both single-country and multi-country estimates of this nexus. The results of the single country estimate are at best mixed across the various frequencies. The study recommends that policymakers in the studied economies should take into consideration these empirical findings when designing policy tools to achieving the correct mix of energy that will stimulate economic growth without causing havoc to the environment.

The results of the panel Granger causality estimates in the frequency domain suggest that a bi-directional relationship exists between energy consumption and economic growth in Africa economies. This implies that to achieve economic growth, the energy sector should be enhanced, and that enhanced energy space will further drive or stimulate growth. The results further suggest the existence of a one-way causality from energy consumption to carbon emissions, ruling out the validity of the conservation hypothesis in these economies. This could be a result of heavy dependency/consumption of non-renewable energy in the region. It is therefore recommended that policymakers in this region should start looking at movement toward clean energy consumption. Our results are in line with the findings of Aydin (2019 for OECD economies, Gorus and Aydin 2018 for MENA economies, but contradicts [33,97].

The study is not an all-inclusive one, as there are limitations, which could be areas to be considered by other studies. For instance, alternative estimation techniques could be employed, other variables like ecological footprints, macroeconomic variables like foreign direct investment, and socio-political variables, among others. Other studies could examine the cost-benefit analysis of different energy options as they relate to the environment, economic growth, among others. Future research can employ multi-criteria analyses useful for quantifying the nexus between the different components.

The global economy is moving towards adopting renewable energy with the intension of mitigating climate change and reducing CO_2 emissions; hence, the economies of Africa should make concerted efforts to develop their renewable energy potential to support economic growth. This is in line with the UN resolution of the 2015 Paris Agreement that by the 21st Conference of Parties (COP21) of the United Nations Framework Convention on Climate Change (UNFCCC), countries should focus on investing in sustainable energy and de-emphasizing the consumption of fossil fuel, among others. African economies are encouraged to formulate and implement policies that will encourage consumption of renewable energy technologies such as laws protecting the production and usage of domestic solar panels, wind turbine production, granting tax incentives to renewable energy investments, stimulate green bonds and investment, among others.

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Data Availability Statement: The data for the study are sourced as follows: CO_2 and RGDP from World Development Indicators (various issues), agriculture value addition and forest areas from Food and Agricultural Organization (various issues), and energy consumption data was from OECD.

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Article

Forecasting the CO_2 Emissions at the Global Level: A Multilayer Artificial Neural Network Modelling

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Abstract: Better accuracy in short-term forecasting is required for intermediate planning for the national target to reduce CO_2 emissions. High stake climate change conventions need accurate predictions of the future emission growth path of the participating countries to make informed decisions. The current study forecasts the CO_2 emissions of the 17 key emitting countries. Unlike previous studies where linear statistical modeling is used to forecast the emissions, we develop a multilayer artificial neural network model to forecast the emissions. This model is a dynamic nonlinear model that helps to obtain optimal weights for the predictors with a high level of prediction accuracy. The model uses the gross domestic product (GDP), urban population ratio, and trade openness, as predictors for CO_2 emissions. We observe an average of 96% prediction accuracy among the 17 countries which is much higher than the accuracy of the previous models. Using the optimal weights and available input data the forecasting of CO_2 emissions is undertaken. The results show that high emitting countries, such as China, India, Iran, Indonesia, and Saudi Arabia are expected to increase their emissions in the near future. Currently, low emitting countries, such as Brazil, South Africa, Turkey, and South Korea will also tread on a high emission growth path. On the other hand, the USA, Japan, UK, France, Italy, Australia, and Canada will continuously reduce their emissions. These findings will help the countries to engage in climate mitigation and adaptation negotiations.

Keywords: CO_2 emission; artificial neural network model; forecasting; simulation

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1. Introduction

There is wide consensus among scientists and policymakers that global warming as defined by the Intergovernmental Panel on Climate Change (IPCC) should be pegged at 1.5° Celsius above the pre-industrial level of warming in order to maintain environmental sustainability [1]. The threats and risks of climate change have been evident in the form of various extreme climate events, such as tsunamis, glacier melting, rising sea levels, and heating up of the atmospheric temperature. Emissions of greenhouse gases, such as carbon dioxide (CO_2) are the main cause of global warming. The Kyoto protocol and the subsequent Paris climate summit have urged the global North and South to cooperate and bear the responsibility of reducing the CO_2 emissions together on a partnership basis. However, climate politics is often not in sync with all the agreements of the Paris climate deals. Especially, since the United States (US) is not a signatory to the Paris climate accords, the international cooperation sought between the industrialized and industrializing countries is slow. Given this broad context of looming climate change threats and the slow pace of actions on reducing CO_2 emissions by the countries, more scientific research must be undertaken to understand the exact nature of the threats. Knowing the level of CO_2 emissions by the high emitting countries in near future will provide actionable insights on climate policy. Such information will aid in fostering the cooperation talks in the upcoming United Nations (UN) COP26 climate conference from 31 October–12 November 2021 in Glasgow, United Kingdom (UK).

Estimating CO_2 has often been done in the context of a school of thought in research, popularly known as the environmental Kuznets curve (EKC) hypothesis. This hypothesis states that environmental degradation, such as air pollution (CO_2, SO_2, NO_2, and SPM emissions), water pollution, and solid waste generation follow an inverted-U relationship with economic growth [2,3]. During the initial level of a country's economic growth, the environmental pollution increases due to rapid expansion in economic activities, however after a threshold level of income per capita in the country is reached, the environmental quality improves because of a higher share of public funds being devoted to improving the environmental quality [4–6]. Despite the last three decades of empirical research in an attempt to estimate the turning point of this EKC, there has still not been consensus about a global turning point. However, there has been tremendous growth in terms of methodological sophistication to estimate both time-series and panel data available for various environmental pollutants and countries [7–12].

A detailed literature review has been undertaken covering the most recent published papers to present the state-of-the-art advancements in EKC studies. Most of these studies have highlighted the role of renewable energy in reducing CO_2 emissions. Dong et al. [13] examined the dynamic causal links among per capita carbon dioxide (CO_2) emissions, per capita GDP, per capita fossil fuels consumption, per capita nuclear energy consumption, and per capita renewable energy consumption for China. They found that both nuclear energy and renewable energy play important roles in mitigating CO_2 emissions in both the short and long run, while fossil fuels consumption is indeed the dominant reason for promoting CO_2 emissions. They observed that renewable energy has a higher CO_2 mitigating effect than nuclear power. Kim and Park [14] from a study of 30 countries for a period of 2000–2013, suggested that a developed financial market in a country helps deploy more renewable energy and, in turn, can reduce CO_2 emissions. Paramati et al. [15] from panel data of G20 countries show that foreign direct investment (FDI) inflows significantly reduces CO_2 emissions in both developed and developing economies while stock market growth reduces in developed economies. They also found that renewable energy consumption substantially reduces CO_2 emissions and increases economic output across the countries in their panels.

In a study, Li et al. [16] used the data from China and Nigeria from 1991–2014 to derive the energy efficiency measures in the mining and extractive related sectors. Using several econometric time series methods, they concluded that energy efficiency in the mining and extractive-related sector and the circular economy have not translated into CO_2 emission reduction in both countries. However, economic growth, energy use (non-renewable energy), and clean energy substitution (renewable energy) are essential factors in mitigating CO_2 emissions. Lorente et al. [17] employed a carbon emission function to investigate the relationship between economic growth and CO_2 emissions in five European Union countries, namely, Germany, France, Italy, Spain, and the United Kingdom, for the 1985–2016 period. They found an N-shaped relationship between economic growth and CO_2 emissions in the EU-5 countries. Further, they observed that renewable electricity consumption, natural resources, and energy innovation improve environmental quality. Using a panel of 20 organisations for economic co-operation and development (OECD) nations for the period, 1870 to 2014, Churchill et al. [18] found support for the EKC hypothesis for the panel as a whole with turning points in income per capita that lie between $18,955 and $89,540 (in 1990 US$).

A study by Chen et al. [19] used the Chinese data for the period 1980–2014 and explored the relationships among per capita CO_2 emissions, GDP, renewable and non-renewable energy production, and foreign trade. They found that there is a long-run relationship among those variables. They also found that China does not follow the EKC for CO_2 emissions under the influence of economic growth, non-renewable energy production, and foreign trade. However, the addition of renewable energy production variables supported the U-shaped EKC hypothesis in the long run.

Using data for 1995–2018, pooled mean group-autoregressive distributed Lag (PMG-ARDL) estimator, and heterogeneous causality tests, Gyamfi et al. [20] failed to confirm an N-shaped EKC in the emerging seven, rather they confirm the existence of an inverted U-shaped EKC in the study countries. They suggested the increased use of renewable energy to mitigate pollutant emissions in these countries. Using the data from a study of BRICS economies for the period of 1980 to 2016, Khattak et al. [21] investigated the complex interaction between innovation, renewable energy consumption, and CO_2 emissions, under the EKC framework. They found that innovation activities have failed to disrupt CO_2 emission in China, India, Russia, and South Africa, except for Brazil. They also showed that renewable energy consumption has mitigated CO_2 emission in the BRICS panel, Russia, India, and China but not in South Africa. Further, except for India and South Africa, they observed the EKC hypothesis in all the BRICS economies. Employing a stochastic impacts by regression on population, affluence, and technology (STIRPAT) framework to the data for the period of 1990–2017 from West Asia and Middle East nations, Kihombo et al. [22] probed the effects of technological innovation, financial development (FD), and economic growth (GDP) on the ecological footprint (EF) controlling for urbanization. They observed that a 1% upsurge in technological innovation decreases EF by 0.01%. However, a 1% rise in FD boosts the level of EF by 0.0016%, inferring that FD stimulates ecological degradation. They also showed the EKC hypothesis in the selected countries.

In India's case, using data for a period of 1990–2015 and several time series econometric models, Kirikkaleli and Adebayo [23] found a long-run cointegration relationship between consumption-based carbon dioxide emissions and its possible determinants. They also found that public-private partnership investment in energy makes a positive contribution to consumption-based carbon dioxide emissions in the long run. Further, public-private partnership investment in energy and renewable energy consumption also significantly causes consumption-based carbon dioxide emissions at different frequency levels in the country. Using annual data from six South Asian economies for a period of 1980–2016 and autoregressive distributed lag (ARDL) regression, Murshed [24] examined the validity of the greenhouse emissions-induced EKC hypothesis, controlling for liquefied petroleum gas (LPG) consumption, FDI inflows, and trade openness. The analysis confirms the authenticity of the EKC hypothesis for Bangladesh, India, Sri Lanka, and Bhutan. They suggested fuel-diversification policies for the government's of these countries. Using the data for a period of 1995–2017 from 34 high-income countries from three continents (Asia, Europe, and America), Khan et al. [25] explained the nexus of GHG emission with tourism, financial development index, energy use, renewable energy, and trade. They observed a country-level reciprocal connection of GHG with financial development in 11 countries, renewable energy in 22 countries, trade openness in five countries, and tourism in 12 countries. Using two-panel data sets of 17 major developing and developed countries as well as six geo-economic regions of the world during 1990–2014, Yao et al. [26] examined the dynamic relationship between renewable energy consumption rate (RER) and the EKC hypothesis. Using several econometric methods, they verified both the EKC and renewable energy Kuznets Curve (RKC) hypotheses, indicating that a 10% rise in RER would lead to a 1.6% carbon emission reduction. Saleem et al. [27] used the data for a period of 1980–2015 from selected Asian countries and employing several econometrics models, found the presence of an EKC hypothesis, where the impact of GDP growth and the square of GDP growth on CO_2 emissions are positive and negative, respectively. They also found that lower-income economies do not support the EKC hypothesis.

Employing the second-generation panel cointegration methodologies and data for 1984–2016, Ahmad et al. [28] analyzed the linkages between natural resources, technological innovations, economic growth, and the resulting ecological footprint in emerging economies. They observed the existence of slope heterogeneity across countries and correlation amongst cross-sectional units. They also found a stable, long-run relationship between the ecological footprint, natural resources, technological innovations, and economic growth. Another study in India by Usman et al. [29] studied the role of energy consumption and democratic regimes in the environmental degradation function for a period of 1971–2014. Using different time series econometric models, they confirmed the EKC hypothesis and divulged that energy consumption increases environmental degradation both in the long and short run. They suggested prioritizing energy conservation policy to mitigate environmental degradation and spur economic growth. Using data from 25 manufacturing subsectors in 38 countries from 2000 to 2014 and using an endogenous finite mixture model, Yang et al. [30] probed the effect of renewable energy in the EKC relationship. They found that with the growing impact of renewable energy consumption, nearly half of the sample countries and two-thirds of the subsectors have experienced the transformation of the nexus between manufacturing growth and emissions. Bilgili et al. [31] employed the panel quantile regression technique on a dataset from thirteen developed countries over the period 2003–2018 to find an inverted U-shaped nexus between economic growth and carbon emissions only in higher carbon-emitting countries, thus, confirming the EKC hypothesis. However, the U-shaped nexus is more predominant in lower carbon-emitting countries. They also found that energy efficiency research and development is more effective in curbing carbon emissions than fossil fuels and renewable energy research and development.

The literature review shows that significant advancement has taken place in the study of EKC in terms of the methods used. In particular, the dynamic time-series and panel cointegration models with the use of structural breaks have produced credible evidence. However, these dynamic time-series models used mostly the lag length to make the model dynamic and estimate the long-run relationship. Moreover, the time series or panel data estimations produce a single estimated parameter for the relationship within the whole sample period. The long-run relationship between CO_2 emissions and its predictors, such as GDP per capita, renewable energy consumption, and trade openness may not have been linear as the previous studies with statistical methods had tried to estimate. A few of the studies used the structural breaks to account for the major shifts in the environmental regulations and policies that may have affected the long-run relationship, but they finally showed constant estimates in observing the effect of GDP on environmental degradation for the whole time period. If the apparent nonlinearities existing in this relationship over a period of time are considered explicitly, more accurate predictions can be made, which has been done in the current study.

The current study aims to forecast the level of CO_2 emissions for 2017–2019 at the global level. CO_2 emission is the key contributor to climate change and there is a global consensus that the mean global surface temperature must be contained at 1.5 degrees C above the pre-industrial level. Consequently, several countries have signed the Paris agreement to reduce emissions within their national boundaries. Against this backdrop, it is essential to forecast the CO_2 emissions levels in the countries that emit a higher share. Such forecasting will help the national governments to adjust their climate policies.

Forecasting of CO_2 emissions at business as usual (BAU) scenario is a necessary tool for major greenhouse gas emitting countries for two main reasons. First, the global circulation models that are used to assess the physical impacts from climate change needs emissions as inputs. Since the countries included in this study are responsible for 79% of global emissions, forecasts of their emission level in the short run will be essential to gauge the impacts of climate change at the global level. Second, the responsibility to reduce CO_2 emissions as agreed at the Paris climate convention is proportional to the BAU levels of emissions. Hence, accurate prediction of emissions will put the right value of resources that these countries need to commit for the reduction of emissions. Since there is a trade-off between emission reduction and economic growth, these countries will be anxious that their emission levels are not underpredicted. Some of the countries may withdraw from a multilateral climate treaty if they find that they are at an economic disadvantage due to their pledge to reduce emissions. Accurate prediction of the BAU emission levels holds significance for a feasible action plan by the countries to reduce the global CO_2 emissions.

Considering that there might be a nonlinear relationship between the indicators of economic growth and the CO_2 emissions, we develop a multilayer artificial neural network (MLANN) model. A multilayer artificial neural network model is more efficient in capturing the nonlinearity present in the time series data and provides higher accuracy in forecasting the CO_2 emissions based on the past values of the emissions and the economic indicators, such as GDP, population density, and urbanization. Such forecasts for the near future will provide insights into regulations on pollution control.

The contributions of the paper are:

(i) Formulation of CO_2 emissions prediction as an optimization problem.
(ii) Development and performance evaluation of MLANN based model for prediction of CO_2 emissions.
(iii) Forecasting of the missing CO_2 emission values for the years 2017–2019.
(iv) Analysis of the results and their economic impact.

The rest of the paper is organized as follows. Materials and methods are discussed in Section 2. Section 3 deals with the development of a CO_2 prediction model using MLANN. Details of the simulation study are given in Section 4. It also contains data collection and preprocessing, training and testing of the model. Section 5 presents results and discussion. Finally, conclusion of the paper is presented in Section 6.

2. Materials and Methods

We have considered two types of countries—first, countries that emit 2% or more share of global CO_2 emissions and countries that emit less than 2% share. The selection of countries in this study is based on the data compiled by the International Energy Agency (IEA), which estimates carbon dioxide (CO_2) emissions from the combustion of coal, natural gas, oil, and other fuels, including industrial waste and non-renewable municipal waste. The specific data used are reproduced from the website Each Country's Share of CO_2 Emissions | Union of Concerned Scientists (ucsusa.org) and are given below in Figure 1.

Table 1 describes the countries considered in this study under two groups—high emission and low emission countries.

Table 1. High and Low emission countries.

Sl. No.	Group 1 High Emission Countries (with ≥2% Share)	Group 2 Low Emission Countries (with 1% Share)
1	China (28%)	Brazil (1%)
2	U.S. (15%)	South Africa (1%)
3	India (7%)	Mexico (1%)
4	Japan (3%)	Turkey (1%)
5	Iran (2%)	Australia (1%)
6	South Korea (2%)	United Kingdom (1%)
7	Saudi Arabia (2%)	Italy (1%)
8	Indonesia (2%)	France (1%)
9	Canada (2%)	

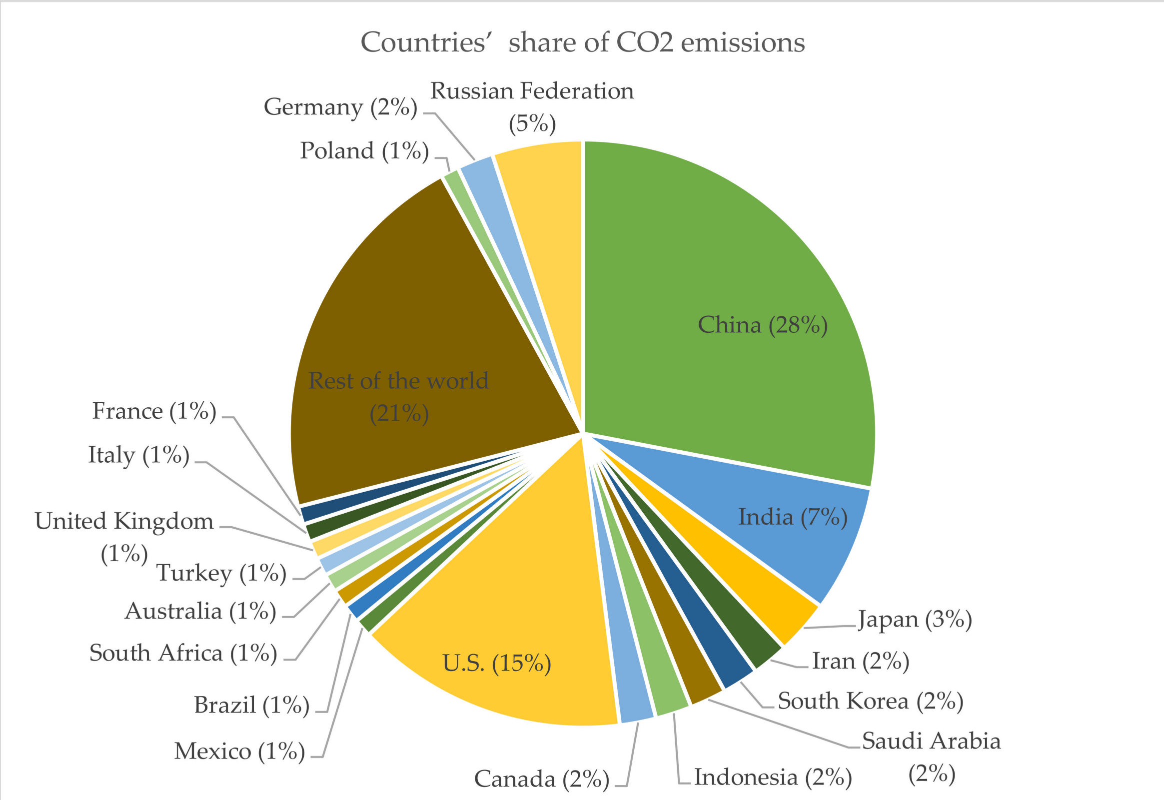


Figure 1. Share of CO_2 emissions in high and low emitting countries.

The data on the output parameter, i.e., CO_2 emissions and the input parameters, such as GDP in constant US$ measured in 2011, trade as a percentage of GDP, and urban population for all the countries are drawn from the World Bank database. The period of the study is 1960 to 2016. The forecasting period is 2017, 2018, and 2019.

Figure 2 shows the GDP (constant in 2010 US$) for the countries considered in this study, in 1990 and 2016. Although the period of study is from 1960 to 2016, we chose the more recent years to compare the growth of the GDP. The countries shown in the *X*-axis are ordered from the highest emission status to the lowest among the 17 countries. The *Y*-axis shows the cumulative annual growth rate (CAGR) between 1990 and 2016. The countries showing a high growth rate in GDP are expectedly China with a CAGR of 9.5%, India with 6.2%, Indonesia with 4.8%, and Turkey with 4.4%. the countries that experienced low growth rates are Italy with 0.7%, Japan with 0.96%, and France with 1.56%.

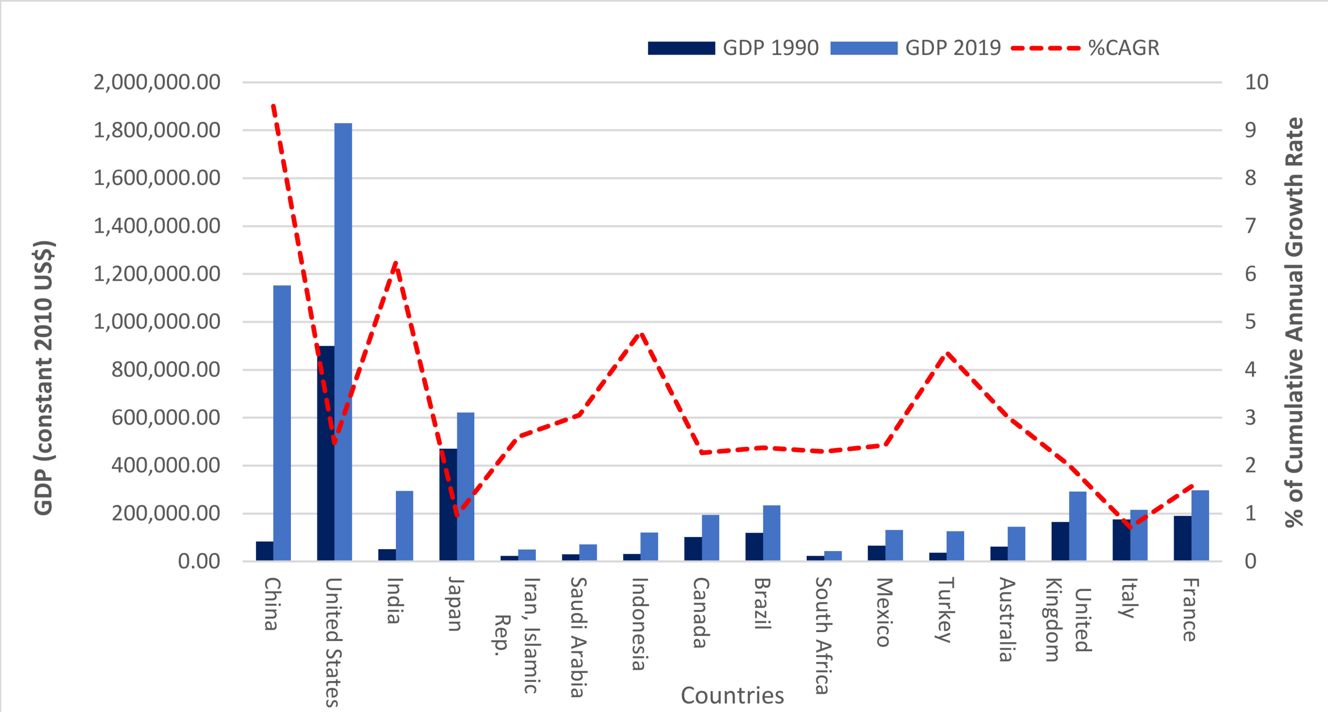


Figure 2. The GDP figures and its growth for the selected countries.

Figure 3 shows the CO_2 emissions of the 17 countries and their CAGR for the period 1990 and 2016. The countries that accounted for the highest growth in CO_2 emissions between 1990 and 2016 are China with 6.17%, India with 5.5%, Saudi Arabia with 5%, Iran with 4.8%, Brazil with 4%, and Turkey with 3.7%. The countries that have managed to rein in their emissions growth are UK with −1.16%, Italy with −1.1%, France with −0.88%, the USA with 0.33%, Japan with 0.41%, and Canada with 0.9%. The growth trends in Figures 2 and 3 suggest that the highly developing countries tend to emit more CO_2 while the already developed countries have slowed down their emissions. This evidence for the period 1990–2016 is close to the assertions of the EKC.

However, future forecasts are needed to convince the developed countries to commit more financial support for the developing countries to motivate the latter to sacrifice some of their economic ambitions. The trade-off that the highly emitting developing countries, such as China, India, and Brazil have to accept to reduce their CO_2 emissions in order to comply with their commitments at the Paris climate summit agreement, is substantial. Unless they receive financial support from the industrialized countries as agreed upon by the Paris climate summit, these countries are unlikely to reduce their emission levels. We attempt to forecast the CO_2 emission levels of 17 countries that account for nearly 79% of the global emissions. By using the highly complex and non-linear artificial neural network (ANN) models that can accurately forecast the future emission values, we provide actionable insights to the policymakers to engage in more active dialogues to achieve the Paris agreement. Using the multilayer ANN model, we forecast the CO_2 emissions for Group 1 and 2 types of countries (Table 1) for 2017–2019.

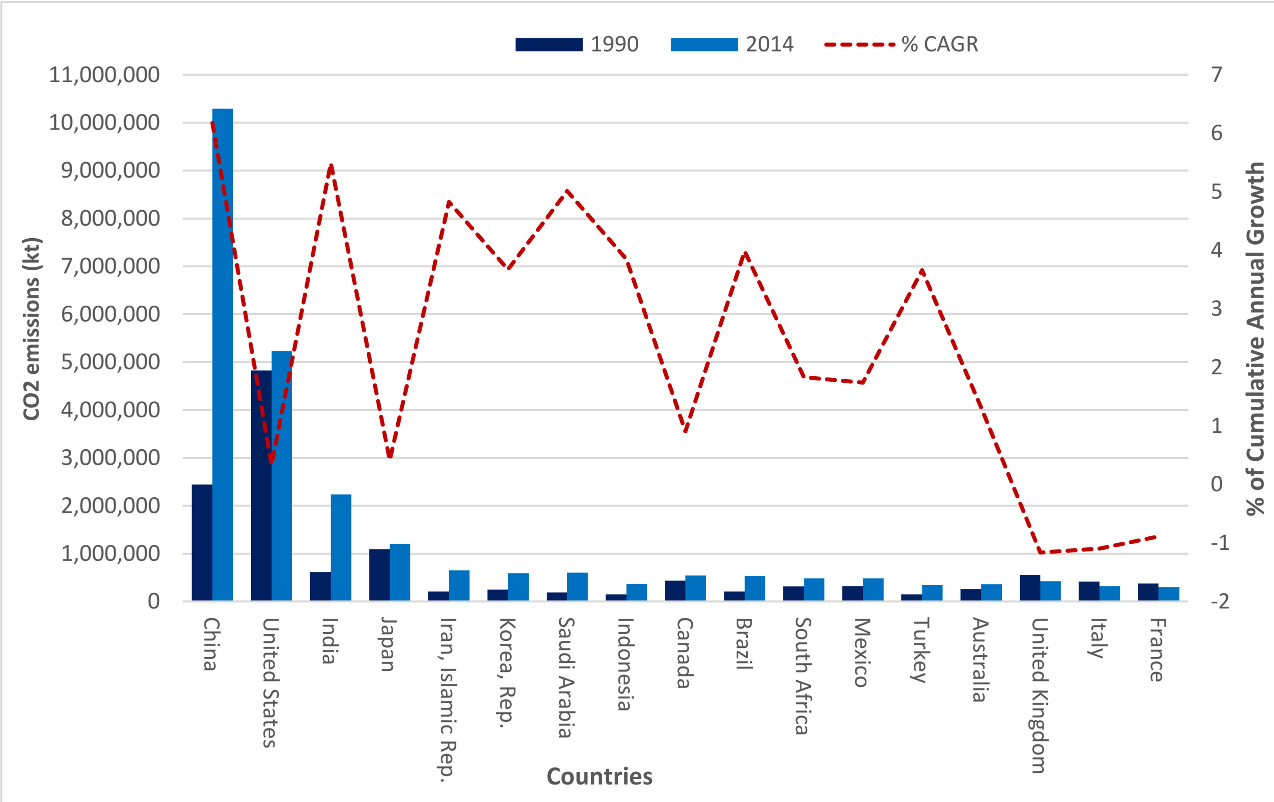


Figure 3. The CO_2 emission (kt) and its CAGR for the selected countries.

3. Development of the Multilayer Artificial Neural Network (MLANN) Based CO_2 Forecasting Model

Statistical models are not able to estimate the relationships accurately when the data are uncorrelated, non-stationary, nonlinear and chaotic [32]. To overcome this problem various intelligent models are proposed by the researchers. The MLANN is a nonlinear, multi-layered, fully connected feedforward network that can model the nonlinearity of the data appropriately [33]. The MLANN model is trained using past data and optimizes the weights that will be used to forecast the CO_2 emissions based on the inputs given. The flowchart shown in Figure 4 is used for the development of a MLANN based prediction model.

The complete structure of the MLANN based prediction model is given in Figure 5. Let $I, J and K$ represent the indices for the input, hidden and output layers respectively. Where I = the number of inputs, J = the number of neurons in the hidden layer, and K = the number of neurons at the output layer. In this CO_2 prediction model the output is one value, so for this study the value of $K = 1$. Let P be the number of input patterns and let any ith input pattern is given as p_i. Each input pattern is supplied to the MLANN model sequentially, multiplied with the weights, sum together, and finally passed through the nonlinear activation function ($tanh$) to produce the output at the first hidden layer. This process is repeated for the next hidden layers and output layer. Let the estimated output of the network is est_k. The error value is obtained by comparing the estimated value with the desired value or target value, t_k. The backpropagation learning rule [33] given in Equations (6)–(11) is used to update the weights and bias values of each layer. This process continues until the squared error is minimum. The detailed equations of feed-forward computation and rules to update the weights and bias are discussed below.

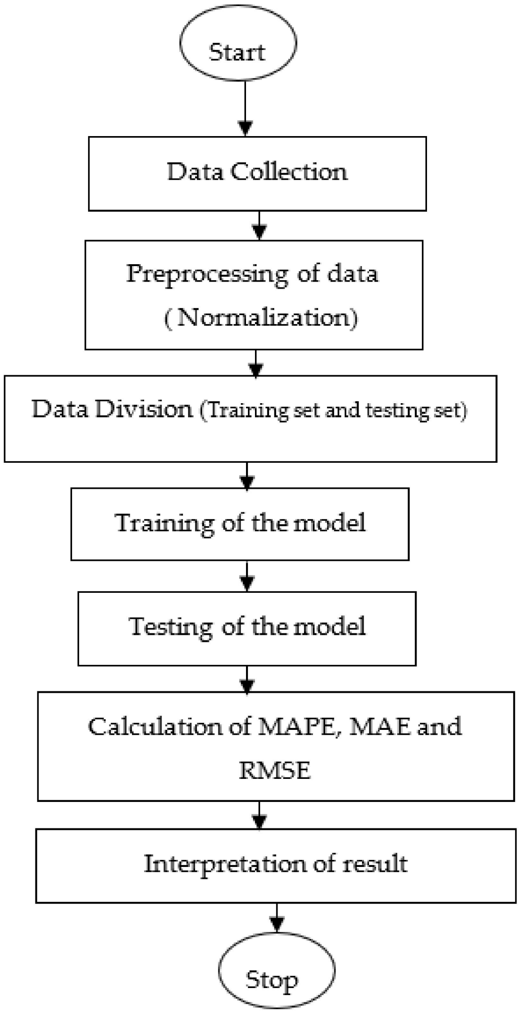


Figure 4. Methodology of MLANN based CO_2 prediction model.

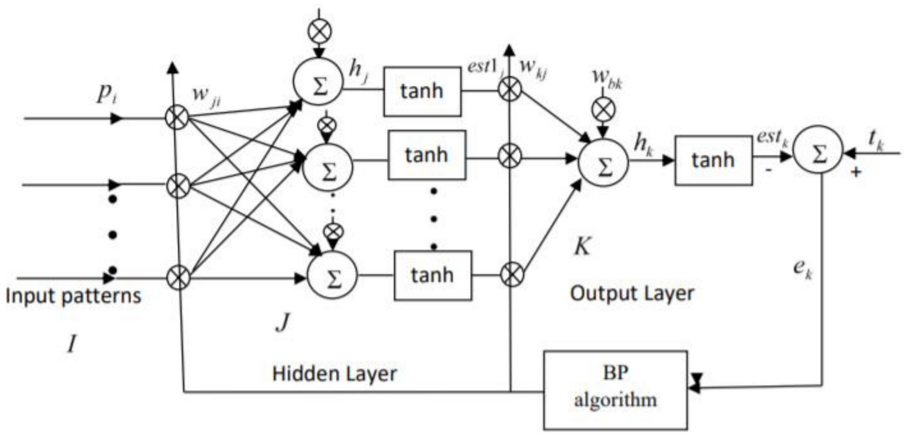


Figure 5. A MLANN based CO_2 emission prediction model.

Refereeing to the above figure, the output of the kth output neuron est_k is given [33] as:

$$est_k = \tan h(h_k) \tag{1}$$

where

$$h_k = \sum_{j=1}^{J} est1_j w_{kj} + w_{bk} \tag{2}$$

$est1_j$ = the output obtained at jth hidden neuron.
w_{kj} = weights connecting jth hidden neuron and kth output neuron.
w_{bk} = bias at kth output neuron.
In the same way, the output at neuron of jth hidden layer, $est1_j$ is computed [33] as—

$$est1_j = \tan h(h_j) \tag{3}$$

where

$$h_j = \sum_{i=1}^{I} p_i w_{ji} + w_{bj} \tag{4}$$

$p_i = i\text{th } input\ pattern$
$w_{ji} = weights\ between\ i\text{th } input\ and\ j\text{th } hidden\ neuron$
$w_{bj} = bias\ at\ j\text{th } hidden\ neuron$

The error value is obtained by comparing the output of the prediction model, est_k with the corresponding target value, t_k. So,

$$e_k = t_k - est_k \tag{5}$$

The weights connecting the neurons of hidden and output layers, w_{kj} are updated [33] by:

$$w_{kj} = w_{kj} + \mu \times \delta_k \times est1_j \tag{6}$$

where

$$\delta_k = e_k \times \frac{(1 - est^2{}_k)}{2} \tag{7}$$

$$\mu = learning\ parameter, (0 < \mu < 1)$$

The bias weight is updated as:

$$w_{bk} = w_{bk} + \mu \times \delta_k \tag{8}$$

Similarly, the weights connecting the input and the hidden layer neurons, w_{ji} are updated [33] as:

$$w_{ji} = w_{ji} + \mu \times \delta_j \times p_i \tag{9}$$

where

$$\delta_j = \delta_k \times w_{kj} \times \frac{(1 - est1_j{}^2)}{2} \tag{10}$$

The updating of bias weight of jth neuron in the hidden layer is done [33] as:

$$w_{bj} = w_{bj} + \mu \times \delta_j \tag{11}$$

The Equations (1)–(11) are the key equations used in the development of the MLANN based CO_2 forecasting model.

4. Simulation study

The CO_2 emissions prediction is formulated as an optimization problem. The model is having three inputs and one output. The inputs are fed to the model and the obtained output is compared with the available target value until the squared error is minimum. Matlab 2016 package is used for the simulation of the problem.

(a) Data collection and preprocessing:

The data for 9 countries under Group 1 and 8 countries under Group 2 are collected from 1960 to 2016 till which the comprehensive data are available in the World Bank database. CO_2 emissions are used as the output parameter for which the out-of-sample forecasting has been done. The variables, such as GDP (in constant 2010 US$), trade ratio, and urban population are used as the inputs in the MLANN model. The data has been preprocessed as the first step in the modeling wherein the data for all the variables have been normalized. During normalization, each value of the four variables is divided by the corresponding maximum value so that all values can lie between 0 and 1. Normalized data generally makes the learning process and the convergence speed faster. If all features do not have similar ranges of values, then the gradients can move to and fro and take a long time before they can attain the global minimum. To circumvent this problem in the learning process, normalization of the data is necessary. Normalization of the data is followed by preparation of training set and testing set. Randomly selected 80% of data are used for training of the model and the rest 20% of data is used for testing of the developed model. Simulation is carried out by varying the ratio of data division (70:30, 80:20, and 90:10) and an 80:20 ratio is selected finally as it gives the best result. Further, the three missing values of CO_2 emission for the year 2017–2019 are calculated using the optimized weights of MLANN based model.

(b) Training of the model:

Out of the total of 57 patterns (1960 to 2016), the training set consists of 46 patterns that are randomly chosen, and the remaining 11 patterns are used for testing of the calibrated model. An input pattern of data consists of the values of trade ratio, urban population, and GDP. The corresponding CO_2 emission value is the target value for the training of the model. A 9:3:1 structure is used for the simulation. It consists of two hidden layers with nine and three neurons respectively. The connecting weights between the layers and the bias weights are randomly initialized to lie between -0.5 to 0.5. The 9:3:1 structure is fixed after doing experiments by varying different structures of MLANN as it gives minimum error value. In each iteration, one input pattern is given to the model, and feedforward processing is done to get the estimated output from the model. Feedforward processing involves summing the weighted inputs, adding the bias weights, and then passing it through the activation function or nonlinear function (tanh). The estimated output is compared with the corresponding target value to obtain the error. The backpropagation (BP) training algorithm is used to update the connecting weights and bias weights. The value of the learning parameter is taken as 0.1. The same process is repeated until all training patterns are exhausted. This completes one experiment. The experiment is repeated until the mean squared error (MSE) is minimized. The MSE value for each experiment is stored and plotted to observe the convergence characteristics. The final value of connecting weights and bias weights are frozen for testing of the developed model.

(c) Testing of the model:

Once the training process is complete, the developed MLANN based model is ready to be used for evaluation. The 20% of the testing patterns are applied to the model sequentially and the estimated output is noted. The estimated output is compared with the corresponding desired value and the mean absolute percentage error (MAPE), mean absolute error (MAE) and root mean square error (RMSE) are tabulated in Tables 2 and 3 which indicate the performance of the model. The MAPE, MAE and RMSE are calculated using Equations (12)–(14). Also, the comparison of the actual and estimated CO_2 values during testing are plotted and exhibited in Figure 6a–i for Group-1 countries. For Group-2 countries, it is given in Figure 7a–h.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|(t(n) - est(n)|}{t(n)} \times 100 \quad (12)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|(t(n) - est(n)| \quad (13)$$

$$RMSE = sqrt(\frac{1}{n}\sum_{i=1}^{n}(t(n) - est(n))^2) \quad (14)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|(Out_{obs} - Out_{est})|}{Out_{obs}}{\times 100} \text{ where } t(n) = \text{target value}$$

$$est(n) = \text{estimated value}$$

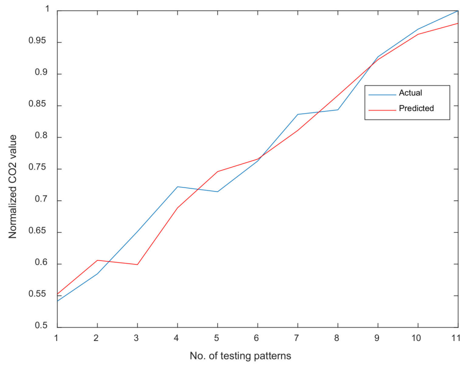
$$n = \text{Number of testing patterns}$$

Table 2. MAPE, MAE and RMSE values obtained during testing for Group-1 countries.

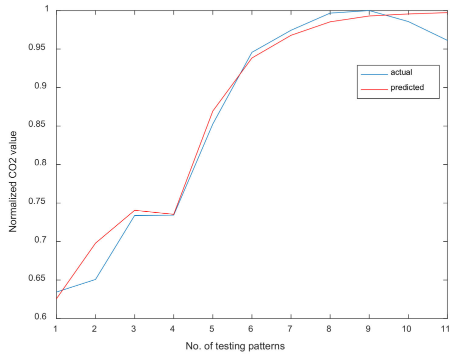
Sl. No.	Name of Country	No. of Total Data Samples Available	MAPE Values(%)	MAE	RMSE
1	India	57 (1960–2016)	2.9287	0.0198	0.0235
2	China	57(1960–2016)	1.7896	0.0113	0.0150
3	Iran	57(1960–2016)	2.3610	0.0262	0.0277
4	South Korea	57 (1960–2016)	2.4803	0.0244	0.0324
5	Canada	57 (1960–2016)	2.9358	0.0244	0.0277
6	Indonesia	57 (1960–2016)	9.6898	0.0767	0.1077
7	USA	47 (1970–2016)	2.7168	0.0265	0.0308
8	Japan	47(1970–2016)	3.5206	0.0214	0.0264
9	Saudi Arabia	49 (1968–2016)	5.9153	0.0462	0.0535

Table 3. MAPE, MAE and RMSE values obtained during testing for Group-2 countries.

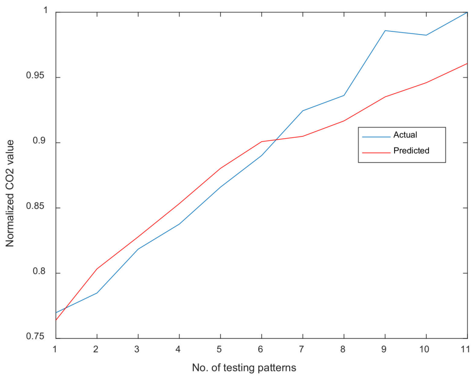
Sl. No.	Name of Country	No. of Total Samples	MAPE (%)	MAE	RMSE
1	Brazil	57 (1960–2016)	5.3345	0.0330	0.0412
2	South Africa	57 (1960–2016)	2.7524	0.0279	0.0379
3	Mexico	57 (1960–2016)	1.9266	0.0200	0.0224
4	Turkey	57 (1960–2016)	2.1538	0.0162	0.0209
5	Australia	57 (1960–2016)	3.4001	0.0367	0.0417
6	UK	47(1970–2016)	3.5419	0.0410	0.0502
7	Italy	45(1970–2014)	8.8015	0.0653	0.0769
8	France	55(1960–2014)	3.8158	0.0241	0.0333



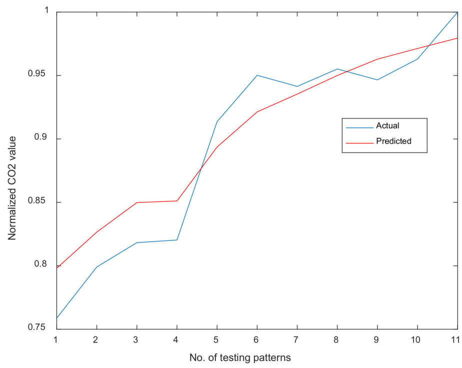
(a) India



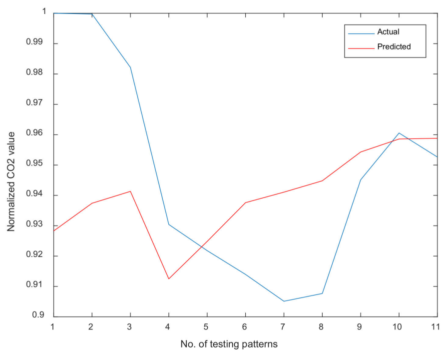
(b) China



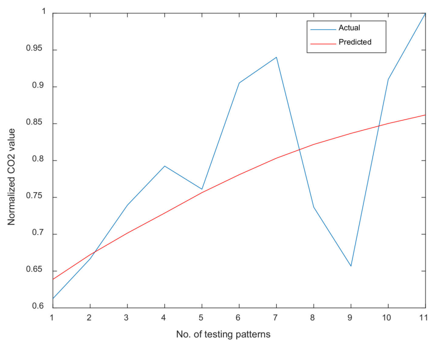
(c) Iran



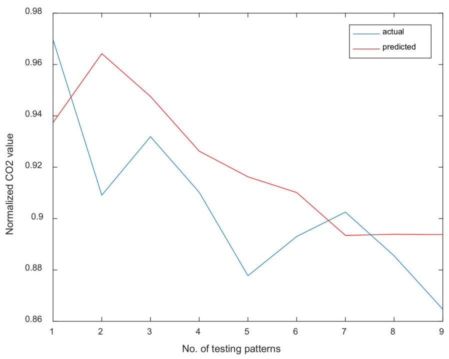
(d) South Korea



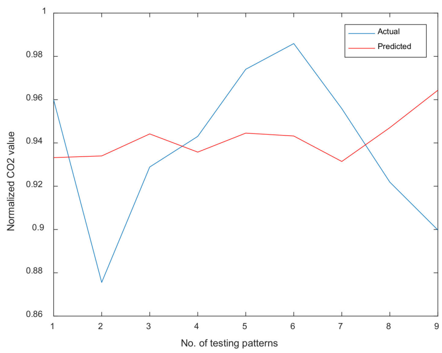
(e) Canada



(f) Indonesia

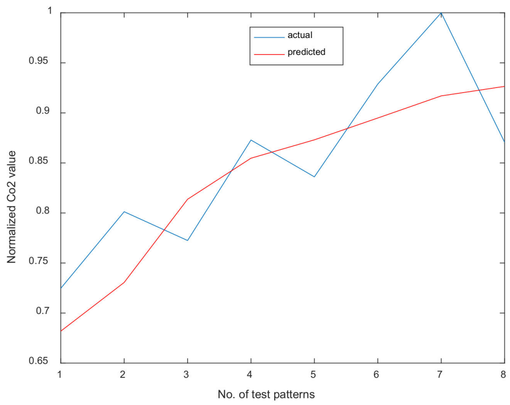


(g) USA



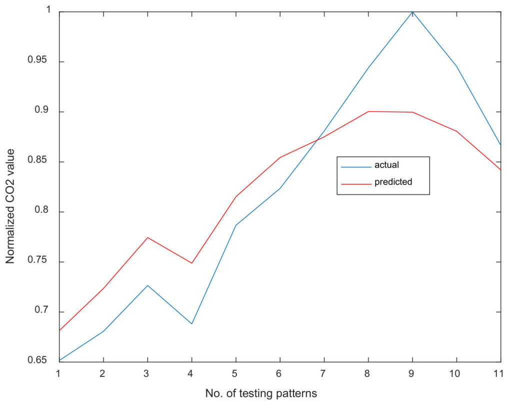
(h) Japan

Figure 6. *Cont.*

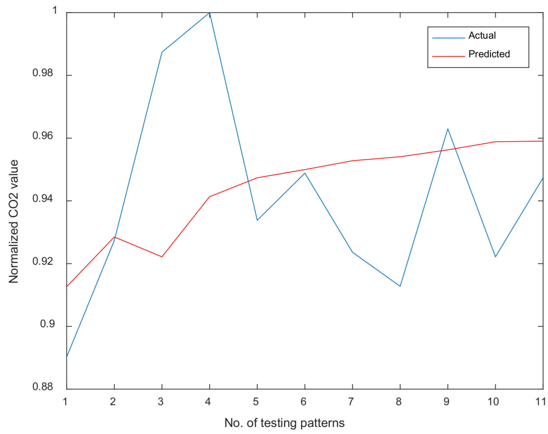


(i) Saudi Arabia

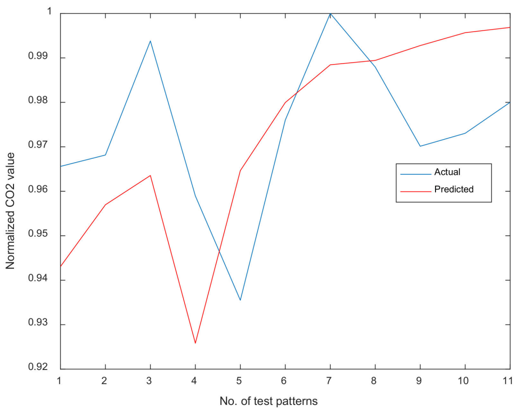
Figure 6. Comparison of the actual and estimated value of CO_2 emissions using the MLANN for Group-1 countries during the testing of the model.



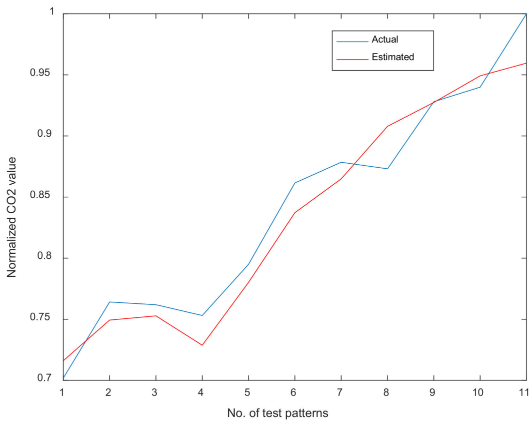
(a) Brazil



(b) South Africa

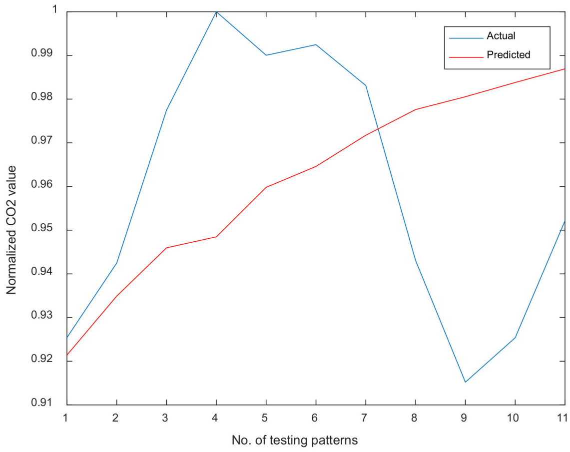


(c) Mexico

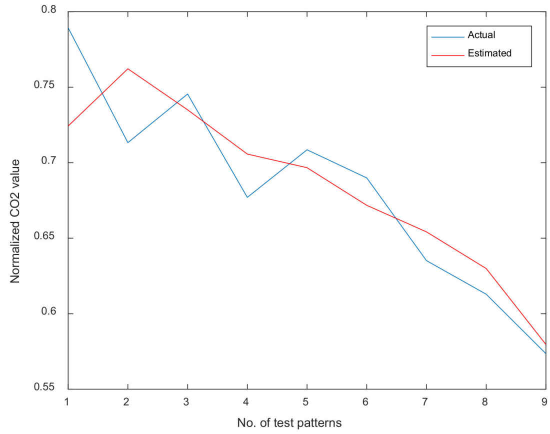


(d) Turkey

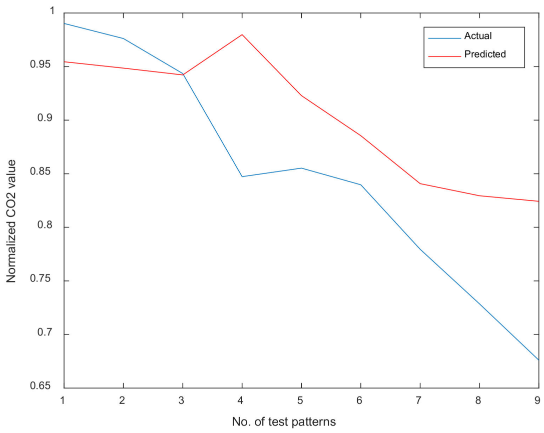
Figure 7. *Cont.*



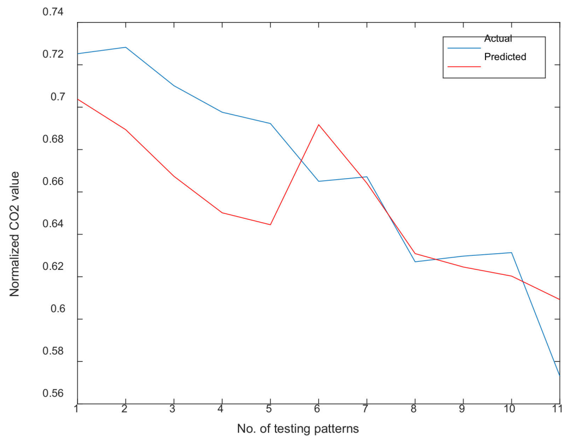
(e) Australia



(f) UK



(g) Italy



(h) France

Figure 7. Comparison of the actual and estimated value of CO_2 emission using MLANN for Group-2 countries during testing.

5. Results and Discussion

From Table 2 it is observed that the MAPE values for Group-1 countries lie between 1.78 to 3.52% except for Indonesia and Saudi Arabia. The MAPE value is 5.91 for Saudi Arabia and 9.68 for Indonesia. The MAPE is an indicator of how close the predicted values are to the actual values. The RMSE values lie between 0.01 to 0.05 for Group I countries except for Indonesia. The MAE values lie between 0.01 to 0.07 for Group I countries. The MAPE values for the Group-2 countries are given in Table 3 which shows that the values lie between 1.92 and 3.8 except for Brazil and Italy. The value is 5.33 for Brazil and 8.08 for Italy. The RMSE values lie between 0.02 to 0.07 and the MAE values lie between 0.01 to 0.06 for Group II countries. As the MAPE values are less than 4% for most of the countries considered in this study, the MLANN model is able to predict the values reasonably accurately with less percentage of error except for a few cases. The comparison of actual and estimated CO_2 values obtained during testing is shown in Figures 6 and 7 for Group-1 and Group-2 countries respectively. In most cases, the actual and estimated values are close to each other.

However, the gap between the actual and predicted values of CO_2 emissions found during the testing phase of the model for Indonesia, Saudi Arabia, Brazil, and Italy is due to the wide fluctuations observed in their emissions data during the period of the study. Although the MLANN model developed in this study is robust to the nonlinearities in the data, wide fluctuations may still increase the percentage of error as is the case for these four countries.

The simulation study is carried out by varying the ANN structure. Different combinations of hidden layer and neurons are used to simulate the model and the results in terms of the training and testing times, as well as the performance achieved, are obtained and displayed in Table S1 in Supplementary Materials. For each country data, initially, combinations of one hidden layer where five, six, seven and eight neurons are used, and thereafter two hidden layers with the same variations of neurons are used for simulation. From Table S1 in Supplementary Materials, it is exhibited that comparing the training time, testing time, MSE in training, and MAPE in testing, the proposed structure of the MLANN model is better in comparison to other combinations of hidden layer and neurons. Further, the simulation is also carried out with different data division ratios and it is observed from Tables S2 and S3 in Supplementary Materials, that the 80–20% ratio is suitable for the proposed study as it gives the minimum MAPE value in all cases.

As suggested in Wu et al. [34], other machine learning methods, such as the support vector machine (SVM) model is simulated and the resultant MAPE values are provided in Table S4 in Supplementary Materials. It is observed that the MAPE values of all countries of Group-I and Group-II are higher in comparison to the proposed MLANN model. We have not added the methods of SVM and a detailed comparison between MLANN and SVM in the main text since it will require substantial expansion of the manuscript.

Forecasting of CO_2 Emissions

In this section, we present the forecasted values of CO_2 emissions for the Group-1 and Group-2 countries for the years 2017, 2018, and 2019 given in Tables 4 and 5 respectively. These are out-of-sample forecasts of CO_2 emissions based on the optimized weights from the calibrated MLANN model and the values for inputs, such as GDP (in 2010 constant US$), urban population, and trade ratio for 2017, 2018, and 2019. The data of CO_2 emissions for these years are not available, however, the data for inputs for these three years are available for most of the countries considered in this study except for Iran, the USA, and Japan. For Iran, input data is available only for 2017, and for the USA and Japan, it is available for 2017 and 2018. Accordingly, the forecasts are done for these countries for the years the input data are available. The EKC hypothesis stands on the empirical evidence that the elasticity of income effect is larger than the combined elasticities of scale and composition effects [35,36]. The literature review in this study has discussed many recent articles that have either established the EKC relationship in the long run or failed to find evidence for it. A few other studies have used a similar framework as EKC to forecast the out-of-sample values of CO_2 emissions [37]. Aufhammer and Carson forecasted the CO_2 emissions for the Chinese provinces for the single year of 2010 by using the estimated coefficient values of different predictors of their 'best' model and the projected values of the predictors, such as GDP per capita and population figures whose values were unknown when they published this study. Two other noteworthy studies by [38] and [39] have used a similar approach and forecasted the time path of CO_2 emissions for the year 2100 and 2050 respectively. We improve upon these studies in two ways. First, we develop a sophisticated neural network nonlinear model to calibrate the EKC relationship and obtain the optimized input weights that are used to predict the CO_2 emissions based on the predictors, such as GDP, urban population, and trade ratios. These optimized weights provide a more realistic time-series relationship between the emissions and the predictors. Secondly, we forecast the CO_2 emissions for high emitting and low emitting countries based on the known values of the predictors, not their projected values.

Table 4. Forecasted CO_2 emission values for the year 2017–2019 for Group-1 countries.

Sl. No.	Name of Country	Year	CO_2 Emission Values (in kt)
1	India	2017 2018 2019	2.3775×10^6 2.3858×10^6 2.3913×10^6
2	China	2017 2018 2019	1.0275×10^7 1.0279×10^7 1.0281×10^7
3	Iran	2017	6.4003×10^5
4	South Korea	2017 2018 2019	6.1217×10^5 6.1490×10^5 6.1616×10^5
5	Canada	2017 2018 2019	5.5083×10^5 5.5332×10^5 5.5369×10^5
6	Indonesia	2017 2018 2019	4.9101×10^5 4.9581×10^5 4.9984×10^5
7	USA	2017 2018	5.0148×10^6 4.8022×10^6
8	Japan	2017 2018	1.2187×10^6 1.2115×10^6
9	Saudi Arabia	2017 2018 2019	5.9955×10^5 5.9752×10^5 6.0329×10^5

Table 5. Predicted CO_2 emission values for the year 2017–2019 for Group-2 countries.

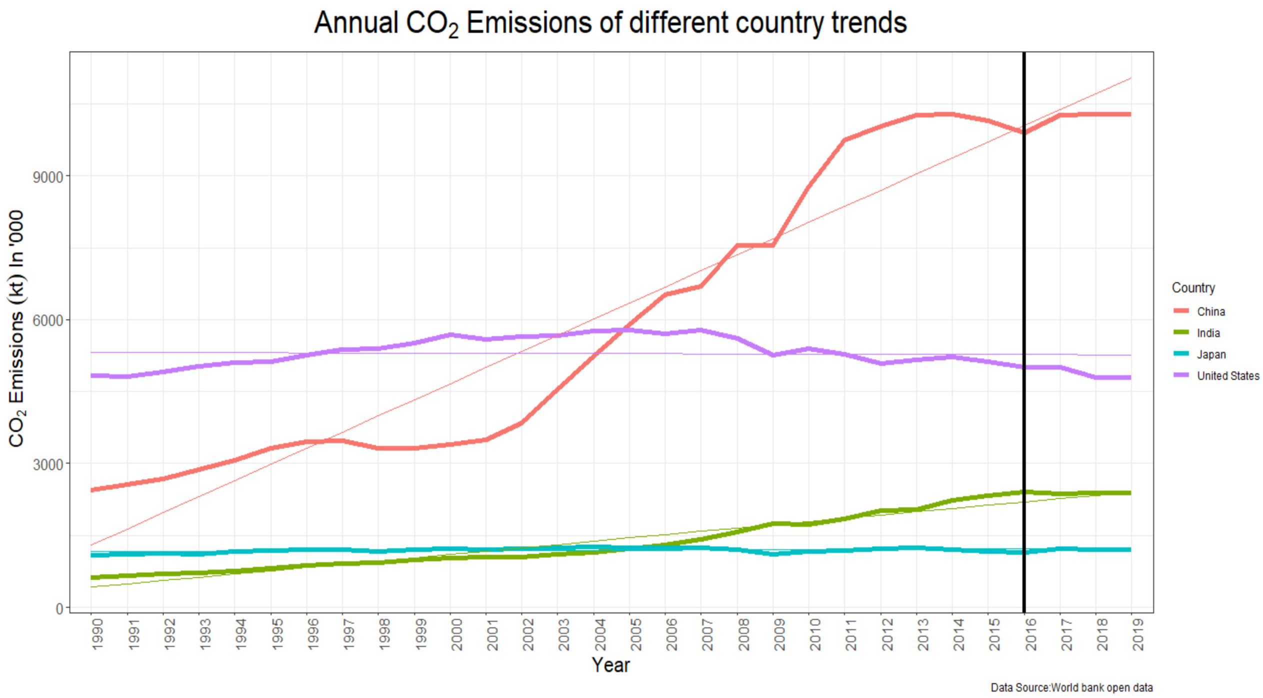
Sl. No.	Name of Country	Year	CO_2 Values (in kt)
1	Brazil	2017 2018 2019	4.5462×10^5 4.7165×10^5 4.7525×10^5
2	South Africa	2017 2018 2019	4.8368×10^5 4.8349×10^5 4.8327×10^5
3	Mexico	2017 2018 2019	4.9500×10^5 4.9521×10^5 4.9517×10^5
4	Turkey	2017 2018 2019	3.6217×10^5 3.6326×10^5 3.6368×10^5
5	Australia	2017 2018 2019	3.9027×10^5 3.9094×10^5 3.9122×10^5
6	UK	2017 2018 2019	3.3021×10^5 2.9951×10^5 2.5307×10^5

Table 5. *Cont.*

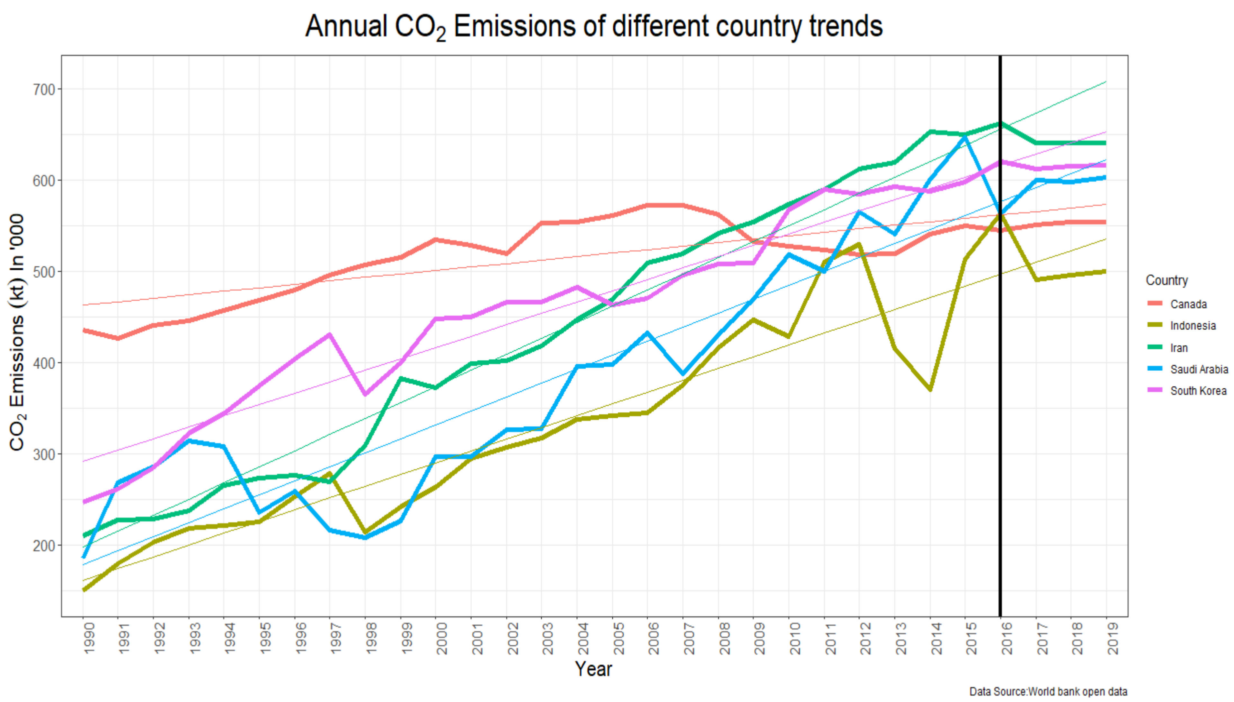
Sl. No.	Name of Country	Year	CO_2 Values (in kt)
7	Italy	2015	3.8895×10^5
		2016	3.9707×10^5
		2017	3.9028×10^5
		2018	3.8698×10^5
		2019	3.8842×10^5
8	France	2015	3.1387×10^5
		2016	3.1091×10^5
		2017	2.9378×10^5
		2018	2.7934×10^5
		2019	2.7095×10^5

Figure 8a,b depict the CO_2 emission values for the Group-1 countries from 2010 to 2019. The emissions from 2010 to 2016 are the actual data obtained from the World Bank database, whereas the values from 2017 to 2019 are the forecasted values. Figure 8a shows that the forecasted emissions for both China and India have increased. China surpassed the USA in 2005 and since then the rate of emission growth is substantially higher for China. During the same period of 2005–2019, the USA's emissions levels have dipped and during the short period of 2017–2019, it shows a declining trend. This is a noteworthy observation in the context of international climate negotiations. Although the USA is not a signatory to Paris climate agreements, it has its internal pollution regulation mandates that have yielded a reduction in CO_2 emissions. On the other hand, China has taken great strides in transforming its economic structure following a circular economy model [40]. Despite these reforms, the emission levels are expected to rise in the short-run horizon. China's past high emission levels and the high growth rate in emission will render it a high emitting country in the near future despite its significant improvement in restructuring the economic models. India is the third highest CO_2 emitter in the world and the rate of emission growth shows a rising trend for the country. The forecasted values for 2017–2019 signify the uphill challenge India is facing to comply with its commitments towards Paris agreements as the emission levels are expected to rise during this period. Japan's emission levels are predicted to reduce further following its declining trend that started around 2007.

Figure 8b shows that the trajectory of CO_2 emissions in Indonesia is quite volatile which is the reason for a higher percentage error in our forecasts for Indonesia. The forecasted values for the period 2017–2019 show arising rend for the country. The other countries in the Group-1 category that shows a rising expected level of CO_2 emissions are Iran, South Korea, and Saudi Arabia. Whereas Canada's emission levels have been stabilized and it embarked on a declining phase of CO_2 emissions since 2008. Figure 9a shows the CO_2 emission trajectory and the forecasted levels for the Group-2 countries. Although the global share of CO_2 emission in countries, such as Brazil, South Africa, Mexico, and Turkey are either 1% or less than 1%, their expected emission level will rise in the near future. Brazil, in particular, shows a high emission growth path which weakens the country's position in the future global climate summits, such as COP26. The reported burning of large tracts of Amazonian forest in Brazil has been heavily criticized by the rest of the globe. The country needs to be more proactive and engaged in complying with its Paris agreement commitments. The expected trajectory of the CO_2 emission growth path for the industrialized countries, such as France, the UK, Australia, and Italy are shown in Figure 9b. The emission levels in France and UK are continuously declining and are expected to decline further. Italy and Australia have reached their peak levels of CO_2 emission in 2006 and 2011 respectively. Since then, their emission levels have stabilized at lower levels and are expected to decline further.

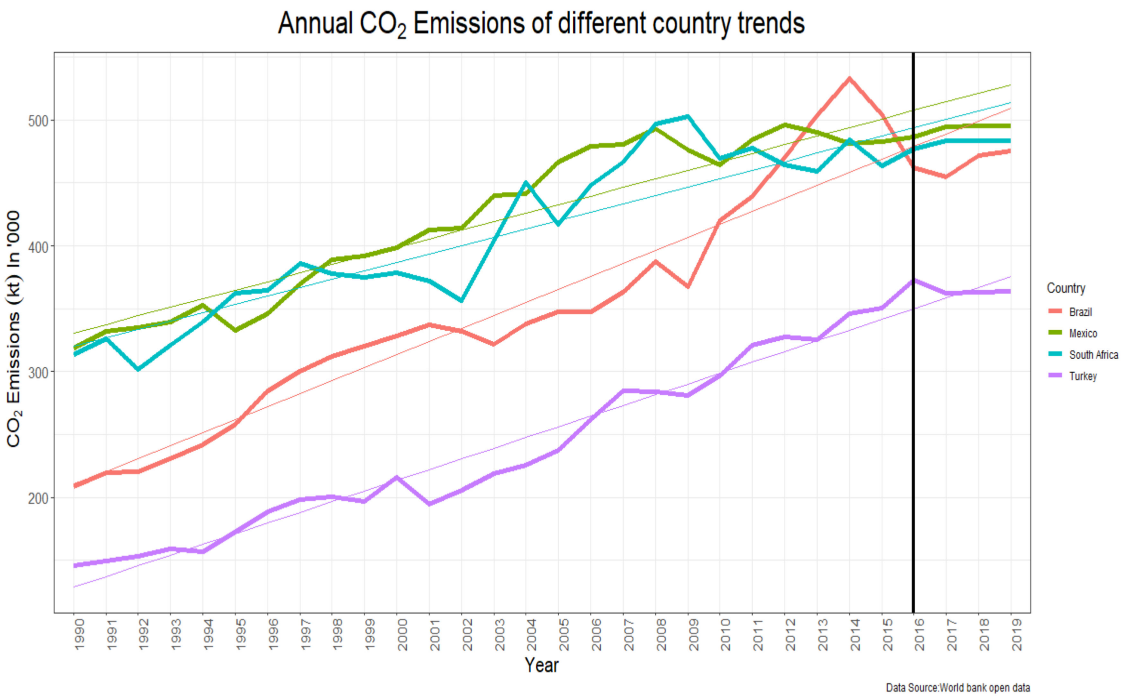


(**a**)

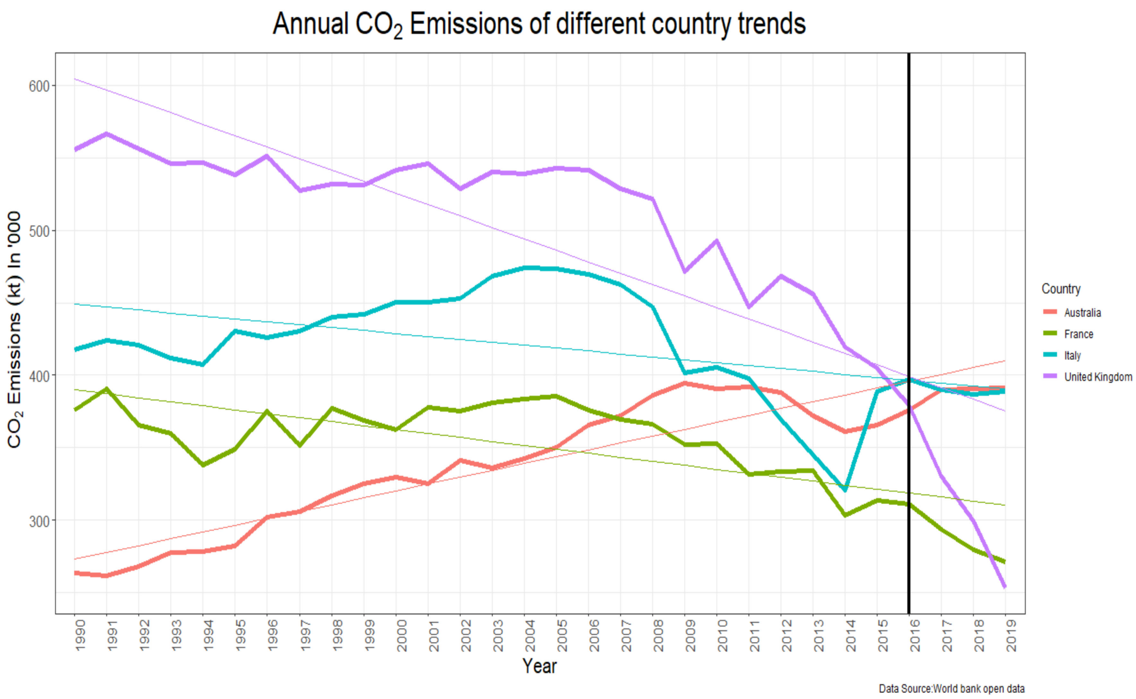


(**b**)

Figure 8. The actual and forecasted CO_2 emissions values for countries: (**a**) China, USA, India, and Japan; (**b**) Canada, Indonesia, Iran, Saudi Arabia, and South Africa.



(**a**)



(**b**)

Figure 9. The actual and forecasted CO_2 emissions values for countries: (**a**) Brazil, South Africa, Mexico, and Turkey; (**b**) Australia, UK, Italy and France.

6. Conclusions

The IPCC report [41] warns that the current level of national pledges on mitigation of greenhouse gas emissions and adaptation to climate change are not enough to constrain global warming to the level agreed upon by the countries in the Paris Agreement. The report urges the signatory countries to upscale and accelerates the implementation of multilevel and cross-sectoral climate mitigation actions. To be able to do so, accurate prediction of future CO_2 emission path in business-as-usual conditions holds importance. Such predictions would lead the countries to accelerate their mitigation and adaptation measures. This study forecasts the CO_2 emissions for the high and low emitting countries by their global shares of emission, for the years 2017, 2018, and 2019. Among the high emitting countries, China and India have been treading a high emission growth path, whereas the US and Japan are on the declining trend. Following the EKC hypothesis literature, we model the CO_2 emissions as the output of the model and GDP in constant 2010 US$, urban population, and trade ratios as the predictors. Several past studies have used the same variables to predict the EKC relationship, however, their methods had been static and mostly linear. Considering that the relationship between CO_2 emissions and its predictors may be nonlinear in the long run, we develop a multilayer artificial neural network model to estimate this relationship.

Based on the World Bank database of 17 countries, of which nine are placed in high emitting (Group-1) and the remaining eight in the low emitting (Group-2) countries spanning from 1960 to 2016, a MLANN model is developed. After the model simulation, it is observed that the prediction accuracy of the in-the-sample data has been 96% leaving 4% to the prediction error. With this high level of prediction accuracy, the model is well calibrated to forecast the out-of-the-sample emission growth path. The data for the input predictors have been available for the years 2017, 2018, and 2019 but not for the CO_2 emissions of the selected countries. Hence, we forecast the CO_2 emissions of these years based on the optimal weights and the input data. From the results, it is observed that China despite its aggressive transformation of economic activities to a circular economy model, is still on the path of increasing emissions in near future. Similarly, India will continue to emit higher levels of CO_2 in the short run that has been studied. Other high emitting countries, such as Iran, Indonesia, Saudi Arabia, and South Korea are expected to continue with their high CO_2 emission growth path if they remain on the BAU economic production-consumption trajectory. These countries need to restructure their economic activities in more sustainable ways to reduce greenhouse gas (GHG) emissions. However, the US and Japan are expected to further reduce their carbon footprint by emitting less CO_2 into the atmosphere. France, UK, Italy, Australia, and Canada are poised to stabilize their emission levels at a low emission growth path and are on course to comply with the Paris agreement. Finally, although low emitting countries, Brazil, South Africa, Turkey, and have been on the rising path of GHG emissions. These countries prioritize their economic growth over the reduction of CO_2 emissions. Hence, they are not expected to comply with the Paris agreement's emission reduction goals.

Based on these results, it is incumbent upon the national policymakers and multilateral policy supporting bodies, such as the UN, OECD, World Bank, and IMF to commit more financial resources for the reduction of CO_2 emissions. Most of the countries that we studied that are on a high emission growth path are currently industrializing. Their goal is to achieve higher economic growth, create more employment, and increase income per capita. Hence, these countries are less likely to change their economic structure suitable for a low carbon economy. The already industrialized countries who have achieved a reduction in their national CO_2 emission goals must come forward to support the countries who are not close to achieving the pledges they made at the Paris climate conference. The next multilateral climate summit which is scheduled to take place in the UK in October-November 2021, known as COP26 will have to focus on issues of greater climate cooperation and finance.

The MLANN model used in the study though has forecasted the CO_2 emission quite accurately in most cases, there are a few cases where the prediction error was high. This is a limitation of the study. Future studies can use other ANN-based models like radial basis function neural network (RBFNN), recurrent neural network (RNN), extreme learning machine (ELM), etc., to reduce the percentage of error. Further, the scope of this study can be expanded by using the mean impact value (MIV) based method to select features and by using the optimal lag order of input data as suggested by Lee and Ou [42] and Wu et al. [43].

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Article

The Dynamics of US Gasoline Demand and Its Prediction: An Extended Dynamic Model Averaging Approach

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Abstract: This study contributes to the body of literature on modeling and predicting gasoline demand by using nonlinear econometric techniques. For this purpose, dynamic model averaging (DMA) and Bayesian model averaging (BMA) combined with Artificial Bee Colony (ABC) are used to forecast gasoline consumption in the United States. The article's independent variables include demographic characteristics, economic activity, income, driving expenditures, automobile price, and road availability for annual data from 1960 to 2020. In the proposed model, not only may the coefficients and elasticity of a predictor of gasoline demand change over time, but other sets of predictors can also emerge at different periods. Moreover, this study aims to automate the process of picking two forgotten variables of the DMA model using the ABC model. Our findings indicate that dynamic model averaging significantly improves forecasting performance when compared to basic benchmark techniques and advanced approaches. Additionally, integrating it with an Artificial Bee Colony (ABC) may result in improved outcomes when time-varying forgetting variables are present. The findings of this research provide policymakers in the fields of energy economics and the environment with helpful tools and information.

Keywords: gasoline demand; dynamic model averaging (DMA); artificial bee colony (ABC); time-varying parameter; dynamic model

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1. Introduction

Gasoline demand in the United States has been steadily increasing since the 1990s. In 2019, Approximately 143 billion gallons of gasoline was used in the United States, with the transportation sector accounting for over 70% of the total consumption [1]. The demand increase can be attributed to factors, such as population growth, urbanization, and increased consumer spending on vehicles. Furthermore, the EIA [1] reported that gasoline demand is highly sensitive to changes in economic activity, fuel prices, and weather patterns. For example, during the COVID-19 pandemic in 2020, gasoline demand in the US fell significantly due to reduced economic activity and stay-at-home orders. However, as the economy recovers and restrictions are lifted, demand is expected to increase once again. In addition, the EIA [1] predicts that gasoline demand will continue to rise in the coming years, reaching approximately 151 billion gallons by 2050.

Numerous research has been conducted on the effectiveness of gasoline demand factors and their capacity to forecast. In this context, some previous studies have adopted a direct approach to estimation by examining the demand for car sales [2–5]. Apart from forecasting vehicle sales, research in the area of travel demand has also looked at gasoline use as a response variable when evaluating fuel price elasticities [6–9]. Huo and Wang [5] discovered that pricing and income elasticities in China are based on consumer vehicle stock and projected vehicle sales in China up to 2050 using the FEEI model. Bento et al. [10] conducted similar research for the United States, using a simultaneous equations model for US households and taking into account the new discarded vehicle markets, among other factors. Graham and Glaister [9] conducted a thorough literature review of 113 studies conducted in the United Kingdom. Goetzke and Vance [11] and Bento et al. [10] found comparable results in terms of fuel consumption's reactivity to fuel prices and in contrast to vehicle mile travel's response to fuel prices. Meanwhile, Oladosu [6] described individual family fuel consumption choices using a vehicle–fuel expenditure allocation model (or AIDS model) for multi-vehicle families in the United States.

In addition, there is a lack of consensus on the estimated coefficients in the studies that have been carried out in the process of modeling and predicting gasoline demand. According to Goetzke and Vance's [11] review of the literature, the average gasoline price elasticity is roughly −0.18, with estimates ranging from −1.01 to 0.01. Thus, the majority of studies interpret these fuel price elasticities as evidence for the existence of a rebound effect, in which the cost savings associated with a reduction in the cost of driving or a gain in fuel efficiency eventually result in an unforeseen rise in fuel consumption. The rebound effect describes a situation in which drivers are presented with lower travel costs (such as falling gas prices) and/or increased fuel efficiency, which unintentionally results in increased fuel consumption and/or vehicle travel. Consequently, in terms of policy, such a phenomenon might result in erroneous calculations and, thus, incorrect interpretations for decision makers. Dimitropoulos et al. [12] conducted a meta-analysis of 74 studies that included 1120 estimates of reported rebound effects and discovered an average rebound effect of 10% to 12%. This unintended impact on driving and fuel consumption habits has significant consequences for the efficacy of policy planning and interventions aimed at reducing emissions and fuel consumption. Overall, studies in the transportation literature employ a variety of methods in terms of model selection, with the majority of scholars being aware of obvious causes for observed discrepancies in the findings. As a result, the effective modeling and forecasting of gasoline demand may offer a critical foundation for policymakers to consider the policy implications of their energy market activities, which is the goal of this paper.

At a minimum, typical forecasting models have two shortcomings: first, numerous studies have shown that predictors change over time, and factors, such as market cycles and macroeconomic policy changes, may result in structural breakdowns in the relationship between fundamental principles and dynamics. Additionally, the effect of each input on the dependent variable changes according to the period and market conditions [13,14]. A model with a static list of predictors may also lose accuracy and consistency over time. Extensive and precise analysis may be performed at any time to pick a model. In other words, if we have N predictors, we must evaluate and compare, 2^N models at each time point (the number of subsets of N variables that accurately represent all possible combinations and inclusions of N variables in the model) with $T \times 2^N$ as the total number of models should be tested throughout T. Therefore, while N and T are large, their analysis is impossible or, at least, difficult.

The accuracy of forecasts has been improved by using model averaging approaches, such as "forecasting combination", in recent research. Both "Bayesian Model Averaging" (BMA) and " forecasting combination" models are characterized by fixed weight values given to models throughout time; however, they do not offer sufficient flexibility to manage the time gap between the contributions of the modeling [15,16]. Therefore, dynamic model selection (DMS) and dynamic model averaging (DMA) were suggested by Raftery et al. [17] to overcome the limitations of the other models. Findings show that macroeconomic forecasting may benefit from this method [18,19]. The appropriateness of each model throughout time is shown in several studies on this subject. The time-varying parameter (TVP) model may employ DMA to compute the average likelihood of each variable being present in the best prediction model. As a more exact definition, one may argue that the average forecast across models is based on an average likelihood of the existence of a variable at time t based on prior knowledge [19–21]. Selecting the optimal prediction model is based on determining which variables have the greatest likelihood of being present in this model, and the model's prediction will be based on this calculation [19]. Although DMS picks a model that comprises variables most likely to be included in forecast models among those estimated in each period, it does so in a more efficient manner. Inspired by the works of Koop and Korobilis [18] and Bork and Mller [22], Raftery et al. [17] found that the DMA model's forecasting accuracy was 30 percent higher than that of other time-series approaches, such as AR and OLS regression. A DMA technique is presented by Wei and Cao [23] to predict a housing price increase in Chinese cities. Research shows that DMA is a better forecasting model than BMA, equal-weighted averaging (EW), and information-theoretic modeling. Dong and Yoon [24] employed a DMA approach to explore the global economic drivers that have a large impact on developing Asian stock market returns, notably during the financial crisis. Moreover, other applications for predicting are noteworthy: aggregate equity returns [25], commodity prices [26,27], exchange rates [28,29], Government bond yields' term structure [27], and commodity price volatility and equity return [30].

Therefore, the following is the study's primary contributions: (1) This study aims to estimate and forecast the gasoline demand in the USA using TVP techniques, particularly the DMA approach, which is much more accurate than prior methods. (2) In most investigations, Bayesian TVP is used to estimate the model's parameters [31,32]. Although this approach approximates the generation of model parameters and switching probabilities using two forgetting elements, the inclusion of forgotten factors might be helpful since full Bayesian models may be quite large and time consuming in terms of computational volume. It also assumes that the two factors are constant over time, which is not the case for the single mechanism addressed in the study by Koop and Korobilis [18]. In addition, removing this constraint to reduce the computing cost of the model may lead to an improvement in model prediction accuracy. In this study, we attempt to execute a random process of forgetting factor selection using an algorithm called the ABC. Therefore, another key contribution in this work is to integrate ABC with DMA to improve the forecast accuracy.

The remaining parts of the article are organized as described below. In the second section, a research approach is presented. In Section 3, we provide a summary of both our data and the empirical findings of the forecasting. The conclusion is presented in Section 5.

2. Research Methodology

The DMA technique employed in the study at hand was introduced by Raftery et al. [17]. The following is the standard models for State-Space approaches, namely the Kalman filter:

$$y_t = z_t\theta_t + \varepsilon_t \tag{1}$$

$$\theta_t = \theta_{t-1} + \mu_t \tag{2}$$

where $\theta_t = \left[\varphi_{t-1}, \beta_{t-1}, \gamma_{t-1}, \cdots, \gamma_{t-p}\right]$ denotes a vector of $m \times 1$ coefficients, and $\mu_t \sim N(0, Q_t)$ and $\varepsilon_t \sim N(0, H_t)$ with a mean of zero and variances of Q_t and H_t are normally distributed. y_t denotes a dependent variable, and $z_t = \left[1, x_{t-1}, y_{t-1}, \cdots, y_{t-p}\right]$ denotes a $1 \times m$ vector of variable interruption and intercept estimators depending on the model. As a consequence, the State-Space method is defined as follows, given a subset of K models at a given time:

$$y_t = z_t^{(k)}\theta_t^{(k)} + \varepsilon_t^{(k)} \tag{3}$$

$$\theta_{t+1}^{(k)} = \theta_t^{(k)} + \mu_t^{(k)} \tag{4}$$

In this equation, $\varepsilon_t^{(k)} \sim N(0, H_t^{(k)})$ and $\mu_t^{(k)} \sim N(0, Q_t^{(k)})$ with $\vartheta_t = (\theta_t^{(1)}, \cdots, \theta_t^{(k)})$ reveal which model of K subsets performs best during whatever period. Dynamic model averaging is a technique that permits a distinct model to be estimated at every given moment [19]. Raftery et al. [17] proposed a DMA approach that involves two parameters of α and λ, dubbed the forgetting factors. A recurrence estimate or forecast is feasible based on the information of conventional filtering when the constants H_t and Q_t are being considered. The following formula serves as the foundation for the Kalman filtering (KF) process:

$$\theta_{t-1}\Big|y^{t-1} \sim N(\hat{\theta}_{t-1}, \sum_{t-1|t-1}) \tag{5}$$

In Equation (5), the calculation of $\sum_{t-1|t-1}$ and $\hat{\theta}_{t-1}$ is performed using a conventional approach that is a function of H_t and Q_t, and then the KF process is performed using the following equation:

$$\theta_t\Big|y^{t-1} \sim N(\hat{\theta}_{t-1}, \sum_{t|t-1}) \tag{6}$$

Since $\sum_{t|t-1} = \sum_{t-1|t-1} + Q_t$, to simplify, Raftery et al. [17] substituted $\sum_{t|t-1} = \frac{1}{\lambda_{t|t-1}} \sum_{t-1|t-1}$ with $\sum_{t|t-1} = \sum_{t-1|t-1} + Q_t$, accordingly with $0 < \lambda \leq 1$, $Q_t = (1 - {\lambda_{t|t-1}}^{-1}) \sum_{t-1|t-1}$. The value of λ_t that is near to one suggests that the coefficients change more gradually. Raftery et al. [17] awarded it a value of 0.99 for the last five years' quarterly statistical data; the preceding figure shows that the observations from the previous five years account for 80 percent of the most current observation. If it is 95%, it indicates that the most recent five years of data accounted for 35% of the weight of the earlier observation. As a result, it is critical to choose the forgetting factors, which are often believed to be between 95 and 99 percent. The estimate in the model will be completed by using updated estimators using the following functions:

$$\lambda_{t|t} = \lambda_{t-1|t-1}$$

$$\theta_t\big|y^t \sim N(\hat{\theta}_t, \sum_{t|t}) \tag{7}$$

In which

$$\hat{\theta}_t = \hat{\theta}_{t-1} + \sum_{t|t-1} z_t \left(H_t + z_t \sum_{t|t-1} z_t'\right)^{-1} (y_t - z_t\hat{\theta}_{t-1}) \tag{8}$$

$$\sum_{t|t} = \sum_{t|t-1} - \sum_{t|t-1} z_t \left(H_t + z_t \sum_{t|t-1} z_t'\right)^{-1} z_t \sum_{t|t-1} \tag{9}$$

Recursive prediction operates based on the predictive distribution in the following manner:

$$y_t|y^{t-1} \sim N\left(z_t\hat{\theta}_{t-1}, H_t + z_t \sum_{t|t-1} z_t'\right) \tag{10}$$

Depending on the model, the above-mentioned functions for k may be expressed as follows, whereas the KF in the fixed estimators' model can be represented as (5)–(7), using ϑ_t as a vector of all parameters (3) and (4).

$$\vartheta_{t-1}\Big|L_{t-1} = k, y^{t-1} \sim N(\hat{\theta}^{(k)}_{t-1}, \sum^{(k)}_{t-1|t-1}) \tag{11}$$

$$\vartheta_t\Big|L_t = k, y^{t-1} \sim N(\hat{\theta}^{(k)}_{t-1}, \sum^{(k)}_{t|t-1}) \tag{12}$$

$$\vartheta_t\Big|L_t = k, y^t \sim N(\hat{\theta}^{(k)}_t, \sum^{(k)}_{t|t}) \tag{13}$$

The value of $\hat{\theta}^{(k)}_t$ and $(\sum^{(k)}_{t|t})$ and $(\sum^{(k)}_{t|t-1})$ was acquired with the use of KF and Equations (8) and (9) and $\sum_{t|t-1} = \frac{1}{\lambda_{t|t-1}} \sum_{t-1|t-1}$. We employed the Raftery et al. [17] technique, which incorporates a forgetting factor termed α for state equations in various estimating models, and so the aforementioned components are analogous to the forgetting factor. Equation (4) is the starting point for the Kalman filter's application. When DMA is utilized, similar effects are obtained:

$$P(\vartheta_{t-1}\middle|y^{t-1}) = \sum_{k=1}^{K} p(\theta_{t-1}^{(k)}\middle|L_{t-1} = k, y^{t-1}) Pr\left(L_{t-1} = k\middle|y^{t-1}\right) \tag{14}$$

The model's prediction function was replaced by the following equation introduced by Raftery et al. [17].

$$\pi_{t\lfloor t-1,k} = \frac{\pi_{t-1|t-1,k}^{\alpha_{t|t-1}}}{\sum_{l=1}^{K} \pi_{t-1|t-1,l}^{\alpha_{t|t-1}}} \tag{15}$$

If $0 \le \alpha < 1$, the interpretation will be identical to that of λ, resulting in the following updated function:

$$\pi_{t\lfloor t,k} = \frac{\pi_{t\lfloor t-1,k}^{\alpha_{t|t-1}} p_k(y_t|\,y^{t-1})}{\sum_{l=1}^{K} \pi_{t\lfloor t-1,l}^{\alpha_{t|t-1}} p_l(y_t|\,y^{t-1})} \tag{16}$$

$$\alpha_{t|t} = \alpha_{t-1|t-1}$$

where $p_l(y_t|y^{t-1})$ indicates the predictive density in terms of y. The weighted mean may be applied to the predictive outputs of each model by using $\pi_{t\lfloor t-1,k}$ to perform recursive prediction on those outputs. As a result, the DMA point prediction is as follows:

$$E\left(y_t\middle|y^{t-1}\right) = \sum_{k=1}^{K} \pi_{t|t-1,k} z_t^{(k)} \hat{\theta}_{t-1}^{(k)} \tag{17}$$

DMS operates in such a manner that it picks the model with the greatest quantity of $\pi_{t\lfloor t-1,k}$ at any point in time. When α equals 0.99, the effectiveness of the previous 5 periods will account for 80% of the weighting for the current time. When α equals 0.99, 80 percent of the weighting for the current period will be determined by the performance of the preceding five periods. When α equals one, $\pi_{t\lfloor t-1,k}$ is precisely determined using the BMA model. Moreover, when λ equals one, BMA uses a traditional linear prediction model with constant coefficients.

Additionally, the suggested model's recursive estimation will begin with past values for $\pi_{0\lfloor 0,k}$ and $\theta_0^{(k)}$:

$$E(y_t|\,y^t) = \sum_{k=1}^{K} \pi_{t|t,k} z_t^{(k)} \hat{\theta}_{t-1}^{(k)} \tag{18}$$

After calculating the equations, period t information is used to update the values. As previously stated, the purpose of including forgotten components is to minimize computational volume, as employing comprehensive Bayesian models may significantly increase computational volume. On the other hand, the sole process provided by Koop and Korobilis [18] is the manual selection of random values, which cannot result in plain values and also presupposes that the two parameters remain constant throughout time. In this work, we attempted to randomize the process for the selection of forgetting factors, α, and λ, using the ABC method. This approach is designed to decrease the sum of squared errors, which indicates the difference between computed and observed data. The mathematical expression is as follows:

$$\text{Minimize } e_t = \left(y_t - E(y_t|\,y^t)\right)^2$$

The following is the pseudocode of the algorithm's implementation procedure:

- Step 1: Choose a curve fitting function. Equations (16) and (18) may be combined to create the following function:

$$E(y_t|\,y^t) = \sum_{k=1}^{K} \frac{\pi_{t\lfloor t-1,k}^{\alpha_{t|t}} p_k(y_t|\,y^{t-1})}{\sum_{l=1}^{K} \pi_{t\lfloor t-1,l}^{\alpha_{t|t}} p_l(y_t|\,y^{t-1})} z_t^{(k)} \hat{\theta}_{t-1}^{(k)} \tag{19}$$

whereas recursive prediction operates using predictive distributions in the following manner:

$$y_t|y^{t-1} \sim N\left(z_t\hat{\theta}_{t-1}, H_t + z_t \frac{1}{\lambda_{t|t}} \sum\nolimits_{t-1|t-1} z_t'\right)$$

- Step 2. Arrange the greatest quantity of repetitions (MNC), the total number of bees (N), and LIMIT.
- Step 3. Create random numbers for all bees for whom the optimization procedure begins with a preliminary estimate of their food supply, s, source using Equation (21).

$$_s w_j^{new}{}_s = w_j^{low} + \gamma(w_j^{up} - w_j^{low}), \begin{array}{c} w^{low} \le w_j \le w^{up} \\ s = 1, \ldots, SN \end{array} \tag{20}$$

where SN represents the food supply in total. w_j^{up} and w_j^{low} represent the top and lower limits of the $j-th$ design variable, while γ is a random real value between zero and one.
- Step 4. Calculate the objected function for all bees using Equation (19).
- Step 5. Select fifty percent of the finest feeding places and appoint the bee who frequented these areas as the engaged bee.
- Step 6. Set cycle = 1.
- Step 7. Traverse each source of food $(i = 1, \ldots, SN)$
  (a) Create new options for an employed bee using the following equation, where a new candidate food source ($_s w_j^{new}$) is identified using two prior food source locations remembered by an employed bee ($_s w_j^{old}$) and a randomly chosen neighborhood of a food source ($_s w_k^{old}$):

$$_s w_j^{new} = {}_s w_j^{old} + \varphi({}_s w_j^{old} - {}_s w_k^{old}) \tag{21}$$

  (b) The old superscript displays the value of the preceding iteration's design variable, but the new superscript displays existing design variables, where φ is a random positive integer between -1 and 1. k is a number that is chosen at random and is not equal to s.
  (c) Select the ideal dietary intake for each food source. The new place becomes the food source if there are more food sources there than there were at the previous location; otherwise, the previous location remains the food source.
- Step 8. Estimate probability (p_i) using the following equation:

$$p_i = \frac{\varnothing_i}{\sum_{i=1}^{SN} \varnothing_i}$$

where $\varnothing_i$ represents a measure of the solution's fitness i, as determined by the employed bee. This corresponds to the nectar content in the food supply at location i.
- Step 9. Traverse each source of food $(i = 1, \ldots, SN)$.
  (a) Employ unemployed bees.
  (b) Utilizing Equation (21), develop novel employment strategies for jobless bees.
  (c) Check to see whether the amount of food sources has improved. If there is a considerable change, the observer bee will be promoted to the hired bee

position; if there is no change, the candidate food source that the observer bee visited will not be selected.

- Step 10. When the best food spot has not improved after a certain number of cycles (LIMIT), the hired bee switches to scout mode and uses Equation (20) to look for a new food source.
- Step 11. cycle= 1 + cycle.
- Step 12. Stop the operation if the cycle is $\geq$ MNC; otherwise, go on to Step.

Another objective of this study aimed to compare the effectiveness of various prediction methods. The Mean Absolute Forecast Error (MAFE) and the Mean Squared Forecast Error (MSFE) are employed as standard indices in this research.

$$\mathrm{MSFE} = \frac{\sum_{\tau=\tau_0}^{T} [y_\tau - E(y_\tau | \mathrm{Data}_{\tau-h})\,]^2}{T - \tau_0 + 1} \tag{22}$$

$$\mathrm{MAFE} = \frac{\sum_{\tau=\tau_0+1}^{T} |y_\tau - E(y_\tau | \mathrm{Data}_{\tau-h})\,|}{T - \tau_0 + 1} \tag{23}$$

where $\mathrm{Data}_{\tau-h}$ is the data that were obtained from the time $\tau - h$, h is the horizon for time prediction, and $E(y_\tau | \mathrm{Data}_{\tau-h})$ is the forecast point of y_τ. This study begins with the results of DMA and DMS, followed by the events that determine which variables are most suited for predicting the gasoline demand function. Then, the performance of DMS and DMA is contrasted. In addition, it assesses the sensitivity of models and prediction results concerning the selection of forgetting factors.

3. The Estimated Model and Data

Annual observations for the United States from 1960 to 2020 were utilized in this analysis. Exogenous variables include measurements of demographic traits, economic activity, income, driving expenses, car pricing, and road availability. These variables in Table 1 are chosen based on an extensive review of the available literature.

Table 1. Research literature for estimating gasoline demand function to determine model variables.

Author	Type	Dep. Variable	Ind. Variable
Hughes et al. [33]	Time series OLS	Fuel demand/capita	Gas price
Wadud et al. [34]	RE panel (quarterly)	Fuel demand	Gas price
Rentziou et al. [35]	SURE panel model (annual)	State VMT	Gas price
Lin & Prince [36]	Dynamic times series	Fuel demand/capita	Gas price
Wang & Chen [37]	SEM (daily)	Household VMT	Gas price
Dillon et al. [38]	SEM (daily)	Household VMT	Gas price
Hymel & Small [39]	Simultaneous equations	State VMT	Fuel cost/mile
Levin et al. [40]	FE panel (daily/monthly)	Fuel demand/capita	Gas price
Dimitropoulos et al. [12]	Lit. review/meta-analysis	Fuel demand & VMT	Gas price
Taiebat et al. [41]	microeconomic model (daily)	Household VMT	Gas price
Gillingham [42]	Lit. review/Lit. survey	US VMT	gas price
Goetzke & Vance [11]	pooled OLS	Household VMT	Gas price
Chakraborty et al. [43]	OLS regression	TOT hh VMT	fuel cost (non-PEV)

Table 2, below, provides a brief description of the variables included in our analysis, as well as a definition and reference to the source. Moreover, summary statistics for the variables that are used in the empirical analysis are presented in Table 3.

Table 2. Variables and definitions.

Variable	Definition	Source
GU/POP	$GU/POP = \ln(\frac{GU}{population})$ GU = Motor gasoline total end-use consumption	EIA
DPI/POP	$DPI/POP = \ln(\frac{DPI}{population})$ DPI = Disposable personal income, Billions of Dollars	FRED
RPR	$RPR/POP = \ln(\frac{RPR}{population})$ RPR = Unleaded Regular Gasoline, U.S. City Average Retail Price	EIA
EFE	$EFE = \ln(FE)$ FE = All Motor Vehicles Fuel Efficiency (Miles per Gallon)	EIA
LD/POP	$LD/POP = \ln(\frac{LD}{population})$ LD = Total Licensed Drivers	FHWA
VR/POP	$VR/POP = \ln(\frac{VR}{population})$ VR = Total Motor Vehicle Registrations For All Motor Vehicles	FHWA
ORP/POP	$ORP/POP = \ln(\frac{PR}{population})$ PR = Public Road Mileage	FHWA

FRED: Federal Reserve Economic Data; https://fred.stlouisfed.org, accessed on 20 June 2022; EIA: Energy Information Administration; https://www.eia.gov/, accessed on 20 June 2022; FHWA: Federal Highway Administration; https://highways.dot.gov/, accessed on 18 June 2022.

Table 3. Descriptive statistics.

	Mean	Median	Maximum	Minimum	Std. Dev.
GU/POP	9.252	9.269	9.408	8.995	0.095
DPI/POP	2.587	2.857	3.970	0.737	1.006
RPR	0.048	0.152	1.293	−1.191	0.783
EFE	2.708	2.797	2.901	2.477	0.158
LD/POP	−0.462	−0.401	−0.359	−0.727	0.112
VR/POP	−0.381	−0.290	−0.173	−0.889	0.208
ORP/POP	9.655	9.655	9.888	9.453	0.142

4. Results

By comparing DMA predictions, we examine forecast performance. We attempted to empirically test several configurations of the ABC model to increase the accuracy of the forecast while achieving the quickest feasible computation speed. In conclusion, the number of bees was fixed at five, the greatest quantity of repetitions at five, and the lower and upper bound between 0.9% and 1%. Finally, we demonstrate the sensitivity of our findings to the choice of forgetting factors, α and λ. We provide findings for prediction horizons of one year (h = 1) and four years (h = 4). A prediction horizon of 4 means that we used the values of the independent variables in the previous 4 periods to predict the dependent variable in the current period. Obviously, with an increase in the prediction horizon, the prediction accuracy of the independent variables decreases. Our models all incorporate an intercept and a single lag between the dependent and independent variables. Experiments with lag lengths up to two revealed that a single lag produces the highest prediction results. Using the ABC approach, we sought to randomize the forgetting components in this study. Thus, our methodology not only provides for the automated determination of the two forgetting elements but also for their evolution over time to minimize the prediction model's inaccuracy. These computations are carried out at a low computational cost. Thus, rather than selecting manually, we use a more precise selection mechanism. Figure 1 illustrates the outcome of estimating the components across time and the prediction horizons one and four. After estimating the model using the combined DMA-ABC model, the chance of each of the model's independent variables being present is supplied. The posterior inclusion probability is shown in Figures 2 and 3. That is, they quantify the likelihood that a predictor will help predict at time t. They are equivalent to the weights applied using DMA to models that incorporate a predictor. These graphs illustrate which predictors are significant at any given moment in time. These graphs demonstrate that DMS nearly always selects sparse models. These results are compelling evidence of model evolution. DMA has a significant theoretical advantage over other forecasting methodologies in that it enables the forecasting model to evolve. Of course, this gain may be negligible in a given empirical application if the forecasting model does not vary much over time. While the same trend remains true to a lesser degree, it is apparent that there is a significant change over time. That is, the forecasting model's collection of predictors evolves with time. After 1980, practically all surface variables enter the model with varying probability. Intermittent values, of course, provide various outcomes. Between 2000 and 2015, the likelihood of existence, or the initial lag, of the majority of model variables is questioned. In comparison to other variables, vehicle registration has the lowest likelihood of being present, while public road mileage at the level and first log values indicate a high possibility of being included in gasoline demand forecasting.

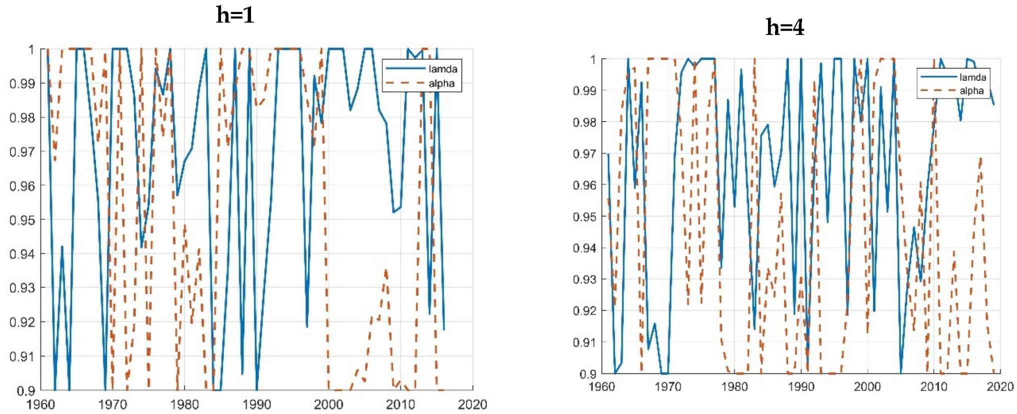

Figure 1. α and λ over time (h = 1, h = 4).

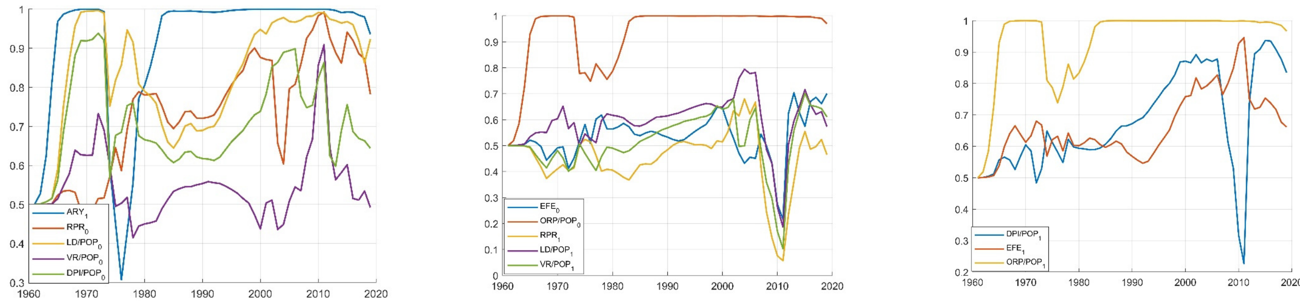

Figure 2. Posterior probability (h = 1).

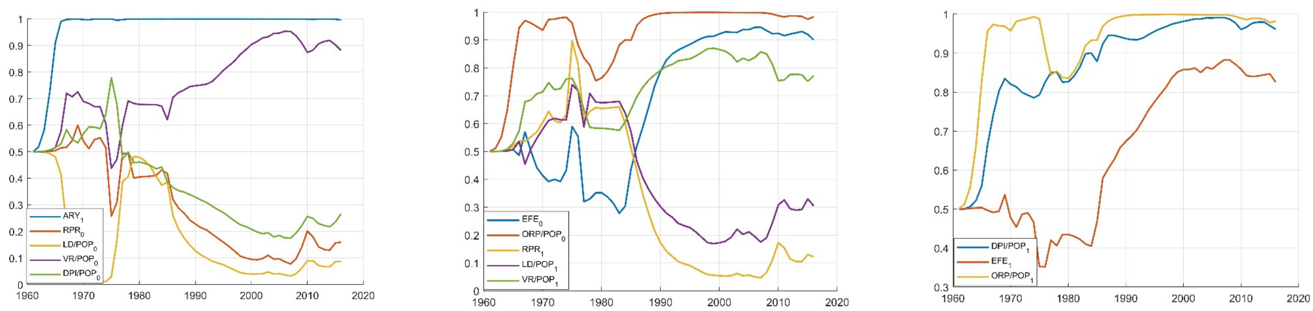

Figure 3. Posterior probability (h = 4).

Figure 4 illustrates the actual and predicted value of gasoline along with the forecast horizons h = 1 and h = 4. The accuracy of the model in estimating gasoline demand is seen in Figure 3. Additionally, expanding the prediction horizon resulted in a decline in the estimated model's accuracy. Our earlier DMA and DMS findings were for our benchmark example, in which we used the ABC technique to determine a random forgetting factor that changes over time. As previously stated, researchers in this area use predetermined values for α and λ. As a consequence, Raftery et al. [17] used $\lambda = \alpha = 0.99$ and suggest that the findings will remain resilient to accepting modifications in these variables. To test these claims of resilience, the results of our forecasting experiment utilizing different combinations of forgetting components are shown in Table 4. MSFE and MAFE values for various models of DMA-ABC, DMS-ABC, DMS, DMA, BMA, TVP-BMA, and TVP are provided in Table 4 for prediction horizons 1 and 4. The results of the comparison of several models in Table 4 indicate that the combined model of DMS and ABC, with the option of automatically acquiring forgetting factors over time, obtains the greatest results in forecasting gasoline demand. According to the DMA-ABC model, the mean values of the forgetting components are equal to α = 0.9449 and λ = 0.9662. Even taking the constant mean values of computational forgetting factors into account produced satisfactory results. It is noteworthy that the value α = 0.9449 enables relatively fast model evolution over time. This is similar to a previous tale we mentioned: it seems that allowing models to evolve is more significant than allowing parameters to vary with λ = 0.9662 for increasing forecast performance. The BME model (with $\lambda = \alpha = 1$) does not have any dynamic approach, which means that while the estimated coefficients are constant over time, the input variables to the model are also constant over time. To investigate the effects of adding dynamics to the model in increasing the forecasting accuracy, we added two more columns to Table 4. In these two columns, the ratio of MAFE and MSFE of different models is calculated with the MAFE and MSFE values of the BMA model (with B index). Based on the results, the prediction error values in model DMS-ABC are about 0.82 of the prediction error in model BMA with a prediction horizon of 1. In addition, this value is equal to 0.76 in the forecast horizon of 4. Therefore, by increasing the prediction horizon, moving towards dynamic models leads to a further increase in prediction accuracy.

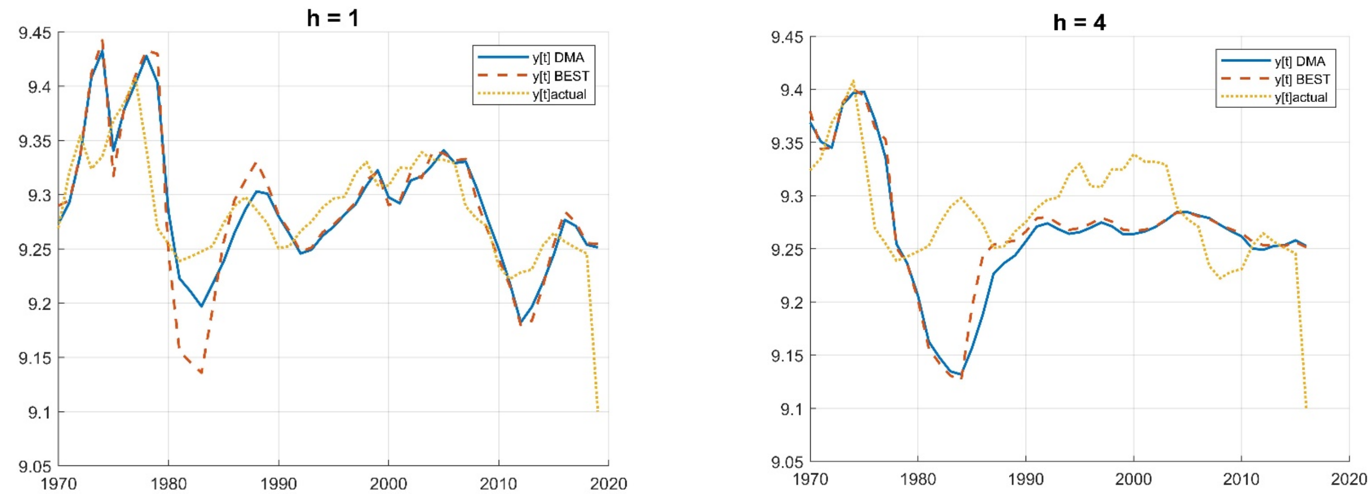

Figure 4. The actual and predicted value of gasoline demand in the forecast horizon h = 1 and h = 4 α = 0.9449; λ.

Table 4. Comparison of models.

Prediction Method	MAFE	MSFE	$\frac{MAFE}{MAFE_B}$	$\frac{MSFE}{MSFE_B}$		MAFE	MSFE	$\frac{MAFE}{MAFE_B}$	$\frac{MSFE}{MSFE_B}$
		h = 1					h = 4		
DMA-ABC	0.55	3.60	1.01	0.98	DMA-ABC	0.71	4.86	0.96	0.96
DMS-ABC	0.47	3.02	0.86	0.82	DMS-ABC	0.58	3.87	0.78	0.76
DMA λ = 0.9662; α = 0.9449	0.53	3.60	0.98	0.98	DMA λ = 0.9698; α = 0.9556	0.71	4.85	0.95	0.96
DMS λ = 0.9662; α = 0.9449	0.44	3.00	0.81	0.81	DMS λ = 0.9698; α = 0.9556	0.58	3.87	0.78	0.76
DMA λ = α = 0.99	0.54	3.65	0.99	0.99	DMA λ = α = 0.99	0.73	5.03	0.98	0.99
DMS λ = α = 0.99	0.45	3.04	0.82	0.83	DMS λ = α = 0.99	0.60	3.98	0.80	0.79
DMA λ = α = 0.95	0.55	3.57	1.01	0.97	DMA λ = α = 0.95	0.72	4.98	0.97	0.98
DMS λ = α = 0.95	0.46	2.99	0.85	0.81	DMS λ = α = 0.95	0.60	3.98	0.80	0.79
DMA λ = 0.95; α = 0.99	0.55	3.56	1.01	0.97	DMA λ = 0.95; α = 0.99	0.72	4.95	0.97	0.98
DMS λ = 0.95; α = 0.99	0.46	2.99	0.85	0.81	DMS λ = 0.95; α = 0.99	0.60	3.93	0.80	0.78
DMA λ = 0.99; α = 0.95	0.54	3.66	0.99	1.00	DMA λ = 0.99; α = 0.95	0.74	5.04	0.99	0.99
DMS λ = 0.99; α = 0.95	0.45	3.04	0.82	0.83	DMS λ = 0.99; α = 0.95	0.60	3.98	0.80	0.79
TVP- BMA (λ = 1)	0.55	3.68	1.00	1.00	TVP- BMA (λ = 1)	0.75	5.08	1.00	1.00
BMA (λ = α = 1)	0.54	3.68	1.00	1.00	BMA (λ = α = 1)	0.75	5.07	1.00	1.00

5. Conclusions and Implications

Accurate modeling and forecasting of gasoline demand may provide a valuable framework for policymakers to consider the policy implications of their energy market activities, which is the goal of this study. The primary shortcoming in prior forecasting models was their inability to accurately predict over time. Policymakers, on the other hand, should disregard short-term and temporary variations in gasoline demand in favor of economic stability. Therefore, the objective of this study was to develop a nonlinear dynamic model DMA-ABS to forecast gasoline consumption in the United States using annual data from 1960 to 2020. These models may be used to determine changes in both the input variables and the parameters of variables through time. The inclusion of two forgetting variables in the DMA model may be used to control the speed of such dynamics in the model, which has been previously determined manually in earlier research. In this work, we sought to implement a random process of forgetting factor selection using the ABC method. Therefore, one of the primary objectives of this study is to merge ABC with DMA to increase prediction accuracy. The findings of the DMS estimation model indicated that the input variables fluctuate with time, emphasizing the need of employing dynamic models rather than constant input variables for estimating gasoline demand.

Gasoline demand prediction helps policymakers to make informed decisions on issues related to energy security, environmental regulations, and transportation infrastructure. For instance, it can assist in determining the number of gas stations required to meet demand in a particular area, the type of fuel to be used in different transportation modes, and the amount of investment needed to maintain or upgrade the transportation infrastructure. Moreover, gasoline demand prediction can aid in managing the price of gasoline. It helps in determining the price level that will meet the demand and supply equilibrium. Therefore, it is recommended that in future research, the DMA model will be integrated with other evolutionary algorithms, such as particle swarm optimization (PSO), genetic algorithm (GA), etc., to compare the results and provide a more accurate prediction of the gasoline market through the expansion of the model presented in this research.

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Assessing Fossil Fuels and Renewables' Impact on Energy Poverty Conditions in Europe

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Abstract: The disadvantages of fossil fuels and their impact on the environment have made the transition to renewable energy sources essential to cover our energy needs. However, different energy resources have a different impact on energy poverty conditions in the world, an issue that is important to examine and properly address. This study examines the impact that fossil fuels final energy consumption in households per capita and renewables and biofuels final energy consumption in households per capita have on energy poverty conditions in Europe, using panel data from 28 European countries for the time period 2004–2019 and static and dynamic regression models, while also performing various econometric tests. The findings indicate that GDP per capita and fossil fuels are linked to an inverse relationship to energy poverty conditions. Renewables and biofuels are also linked to an inverse relationship to the inability to keep homes adequately warm and the presence of leaks, damp, or rot in the dwelling, but they could be considered a driver of arrears on utility bills. In addition, a comparative analysis between Sweden, Germany, and Greece and their conditions on energy poverty and energy transition was conducted, highlighting the differences existing between the three European countries. The findings of the research can be useful for governments and policy makers to develop strategies that promote energy transition while protecting energy consumers.

Keywords: energy poverty; fossil fuels; renewables; Europe

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1. Introduction

The discovery and use of fossil fuels can be viewed as the main foundation of humankind's prosperity, growth, and well-being [1]. Coal, oil, and gas have been in the center of the industrialized world since the early 1800s and they constitute the main driving force of economic and social growth in the world [2]. Fossil fuels are still used to cover most of the world's energy needs and this usage is expected to increase more in the future, due to the expected increase in the global population and the new, energy-intense way of life [3].

The disadvantages that emerge from the usage of fossil fuels are many and significant. Fossil fuels are primarily responsible for enormous greenhouse gas emissions into the atmosphere, and they contribute on a great level to global warming, something that could be proven catastrophic for the environment as well as for human health, life, and civilization as we know it [4]. In addition, fossil fuels are finite, and some scientists believe that they might reach their peak soon [1]. Their depletion means that the world should not rely on them anymore and, instead, turn to alternative sources.

All the disadvantages that come as a result from the use and combustion of fossil fuels make it obvious that the world should focus on alternative energy sources, or other energy saving methods and measures for the mitigation of GHG emissions [5]. A transition to renewable energy sources for the satisfaction of our energy needs is considered to be essential to address climate change and achieve the target of limiting the global average temperature increase under 2 °C. Despite the fact that the usage of renewables has increased over past years, fossil fuels still cover around 80% of global energy demands, leading to an urgent need of change in future energy policies [6].

To achieve a successful full transition to clean energy sources, it is important that energy R&D is promoted on a global level and that innovation, investment, and deployment policies and strategies regarding energy storage technologies are evolved and adopted by policy makers [7]. Cities, which are the biggest energy consumer, should be a part of that transition, promoting a cleaner urban energy system that will lead to cleaner cities [8]. In addition, the transition requires political support and efficient governance, as well as market designs and financial incentives [9]. This transition, unlike other energy transitions that have happened in the past around the world, will have to occur rapidly to successfully tackle climate change. Even though it is supported that this transition is unlikely to happen within the next few decades, governments should promote and support such policies, while international agreements concerning the issue should be implemented [10]. The COVID-19 pandemic that had an important impact on the global economy, has also widened the uncertainty of energy transition [11].

Currently, the world highly depends on fossil fuels. This means that certain features are configured, while they provide stability regarding technological artefacts and scientific knowledge, market structures, practices, and regulatory frameworks [12]. Based on that, a few experts argue that a transition to renewable energy sources would disturb the balance that fossil fuels have provided, and it would challenge the status quo. It is often believed that renewables might not be able to meet the global energy demand, because of their lower energy density, or that society and politicians will not adopt the best scientifically proven alternative that is available. Some experts argue that the implementation of Carbon Capture and Storage (CCS) is the best solution for CO_2 emissions mitigation and sustenance of the fossil fuels use at the same time [13], but it is found to be a more expensive and riskier alternative to renewables, while not being carbon neutral [9]. In the literature, some studies have focused on the social and political impacts of renewables [14], on their impact on social welfare [15], as well as on their impact on local development [16]. However, after taking both positive and negative impacts into consideration, most scientists believe that the transition to renewable energy sources is beneficial and is viewed as the best solution, in order to promote sustainability and energy security.

Energy poverty is another energy-related topic that is well-discussed in the recent literature. It refers to a situation where households do not have access to the necessary energy services, which are vital for the satisfaction of basic human needs [17]. A household can be characterized as energy poor when it is lacking sufficient, affordable, and safe energy services [18], something that is not observed in developing countries only; an important number of European households were found to be "fuel poor", especially during the period of the global financial crisis [19].

The linkages between the different types of energy sources and energy poverty, as well as between energy transition and energy poverty, have not been examined extensively in the existing literature. It is, however, a topic that should be addressed and the studies that focus on this matter could be used as a tool by policy makers for the successful implementation of energy-related strategies and policies, which have been in the center of many global initiatives for sustainability. For instance, the 7th Sustainable Development Goal proposed by the United Nations, referring to providing access to affordable and sustainable energy services for all, includes both the topics of energy poverty and energy transition to more sustainable sources [20]. This study aims to contribute and expand the existing knowledge on the topic, examining the relationship between energy poverty conditions in 28 European countries for the years 2004–2019 and energy consumption coming from fossil fuels and renewables in households, using an advanced econometric methodology.

2. Literature Review

A significant number of studies in the current literature have been focusing on the topic of energy poverty. A review of the problem of energy poverty has been presented by Halkos and Gkampoura; the authors included in their review various definitions that have been given to energy poverty in the literature, as well as the impact that energy poverty has on human health, on the society, the economy, and the environment. In addition, various energy poverty drivers are identified, including household characteristics and other socioeconomic and environmental factors. The authors also analyzed the different approaches to measuring energy poverty and presented the situation currently occurring in different parts of the world regarding the problem. Various actions that could assist in tackling energy poverty are also presented in the review [21].

The main approaches of measuring energy poverty that have been suggested in the literature include the expenditure approach, where metrics are compared to certain thresholds, and the consensual approach, where various indicators that are based on surveys can be used, while composite measurements can also be created [22]. The Multidimensional Energy Poverty Index (MEPI), developed by Nussbaumer et al. [23] is one of these composite indexes, which takes into account the multidimensional nature that energy poverty has, and it was used to estimate energy poverty for certain African countries. Based on the same index, energy poverty was calculated for certain Latin American countries by Santillán et al. [24].

When it comes to European countries, the European Union Statistics on Income and Living Conditions (EU-SILC) provide measures and data that can be used to calculate energy poverty, including the indicators for measuring energy poverty that are suggested in the literature: (i) inability to keep home adequately warm, (ii) arrears on utility bills and (iii) presence of leak, damp, or rot in the dwelling. These data was used by Thomson and Snell [25], who estimated fuel poverty for 25 European countries, by proposing a methodology of four different scenarios, where a different weight was assigned to each indicator. Based on this methodology, Halkos and Gkampoura [26] in their research also created four different scenarios with different weights, in order to evaluate energy poverty conditions in 28 European countries for the period 2004–2019, while identifying the drivers of energy poverty conditions and the impact that the economic crisis had on them.

A stochastic frontier analysis approach was used by Rodriguez-Alvarez et al. [27] to identify the determinants of energy poverty in 30 European countries for the years 2005–2018. The three previously mentioned indicators were also used by Bollino and Botti [19], who combined them with two additional variables, developing the Energy Poverty Multidimensional Index (EMPI) to capture and evaluate energy poverty for 2012 and 2014 in Europe.

In the current literature, a few studies have examined the relationship between renewables and energy poverty, as well as between energy transition and energy poverty. Most of these studies support that a transition from fossil fuels to renewable energy sources will have a positive impact on energy poverty, helping towards its eradication. However, it is also argued in a few studies that energy transition could have negative results on energy poverty-related problems, unless certain measures are being implemented to minimize their damage.

More specifically, Mastropietro [28] analyzed the effect that renewable energy sources for electricity might have on energy poverty. The author argued that the costs required to support renewables' technologies are often transferred to the consumers as surcharges, something that could lead to more intense energy poverty issues. It is suggested that measures, such as state finance or finance through the auctions for emission allowances should be implemented, in order to minimize the social cost that will follow after energy transition.

Specific guidelines that should be followed in order to eliminate the problem of energy poverty by using renewable energy sources and, more specifically, solar energy, were presented by Pagliaro and Meneguzzo [29]. The authors argue that energy poverty will be reduced if renewables are adopted for energy generation and they make specific suggestions to policy makers, such as: view energy poverty within its local social and economic context, get advice from energy managers with knowledge regarding new technologies in the sector and their socioeconomic impacts, make the community engage and be interested in the matter, and establish public institutions concerning renewables, with the target of providing education on the topic and strategies for a successful energy transition. These guidelines, according to the authors, will facilitate the transition process and will lead to environmental and socioeconomic benefits.

The linkages between energy transition and socioeconomic inequalities in Europe have also been explored in Bouzarovski and Tirado Herrero's [30] research, who emphasize the spatial and temporal variations in energy poverty's incidence. The authors found that there are significant regional inequalities concerning the drivers of energy poverty and the exposure of the countries to them, meaning that energy poverty is a problem presented in a variety of social strata. They also pointed out that energy poverty has increased in the EU since 2007 in general, even though energy transition does not have an extreme impact on these inequalities, according to the authors' results. Further investigation concerning the risks that result from energy transition is strongly suggested.

The case of the UK was studied by Hiteva [31], who examined the potential impact that energy transition might have on fuel poverty. The author took into consideration the conditions of energy transition and the costs, risks, and financial liabilities in the industry of renewable energy, that could have a negative effect on energy poverty. The case of the UK was analyzed and then compared with Bulgaria, the country with the biggest percentages of people living in energy poverty conditions in Europe. The author suggested that the issue of fuel poverty should be addressed throughout the whole renewable electricity production chain and not just at the consumption end and highlighted the need of implementing policies for fuel poverty alleviation throughout this chain.

The effect that energy poverty has on several development outcomes was analyzed by Adom et al. [32], while taking into consideration the influence of green energy transition. The findings highlight that a transition to green energy could potentially reduce vulnerability and provide partial resilience regarding energy poverty shocks, while it could also facilitate the improvement of several development outcomes, including GDP per capita, poverty, and income inequality.

Based on these studies found in the current literature, it can be observed that the results regarding energy poverty and different energy sources linkages, as well as energy poverty and energy transition linkages vary, especially when focusing on different world regions. Even though the topic is discussed in the recent literature, it is significantly important to further examine this relationship. This study examines the linkages between energy consumption coming from fossil fuels and renewable sources and energy poverty indicators for 28 European countries, using an in-depth econometric methodology, that is presented in Section 3. To the best of our knowledge, this methodology has not been used in any similar studies, while examining European countries and using recent data at the same time. In addition, a comparative analysis of energy poverty and energy transition conditions in three European countries is conducted, in order to better understand the progress of three countries with different socioeconomic and environmental conditions on these topics.

3. Methodology

For the analysis, data were collected for the three indicators that are considered to be the key elements of energy poverty, according to the current literature (Table 1: Indicators 1–3). In addition, data were collected regarding GDP per capita, final energy consumption in households per capita, as well as final energy consumption in households by fuel (Table 1: Indicators 4–6). These last two databases were combined, in order to create two new indicators: FFpc, which stands for fossil fuels (oil and petroleum products, natural gas and solid fossil fuels) final energy consumption in households per capita, and RESpc, which stands for renewables and biofuels final energy consumption in households per capita. All data were retrieved from Eurostat's database, for the period 2004–2019 and for 28 European countries (Figure 1). Statistical packages EViews and Stata were used for the analysis.

Table 1. Indicators retrieved from Eurostat and used for the analysis.

	Indicators	Measurement	Source
1	Inability to keep home adequately warm	%	[33]
2	Arrears on utility bills	%	[33]
3	Population living in a dwelling with a leaking roof, damp walls, floors or foundation, or rot in window frames or floor	%	[33]
4	Purchasing power adjusted GDP per capita	Purchasing Power Standards (PPS)	[34]
5	Final energy consumption in households per capita	kg of oil equivalent per capita	[35]
6	Final energy consumption in households by fuel	%	[36]

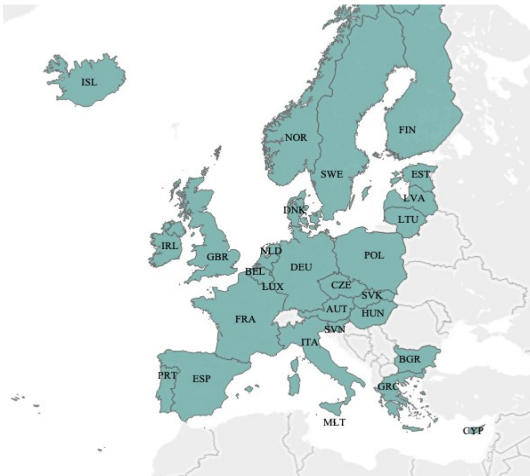

Figure 1. The 28 European countries included in the analysis. (Tableau Software was used for the creation of all presented figures).

The linkages that exist between energy poverty and fossil fuels and renewable energy consumption are examined, taking into consideration panel data for the years 2004–2019. After the use of Box–Cox specifications that compare linear and logarithmic forms, three different regression models are formulated, where Indicators 1, 2, and 3 (Table 1) are considered as dependent variables, and GDP per capita, fossil fuels final energy consumption per capita, and renewables and biofuels final energy consumption per capita are considered as independent variables. The proposed model is:

$$(IndicJ)_{it} = a_{i,t} + \beta_{1i,t}(GDPpc)_{i,t} + \beta_{2i,t}(FFpc)_{i,t} + \beta_{3i,t}(RESpc)_{i,t} + \gamma_i + \delta_t + \varepsilon_{1,t} \quad (1)$$

In this regression model, GDPpc stands for GDP per capita, FFpc stands for fossil fuels final energy consumption in households per capita, and RESpc stands for renewables and biofuels final energy consumption in households per capita. Additionally, J equals to numbers 1–3, indicating the three different indicators that are used as dependent variables.

For the models' estimations, Fixed (FE) and Random (RE) Effects methods are used, depending on how ai is handled: either as fixed predefined numbers or as random expulsions from a particular distribution [26,37–39]. In the case of Fixed Effects, where the cross-section specific components are viewed as fixed parameters, then the model becomes:

$$y_{it} = a + X'_{it}\beta + \sum_{i=1}^{N} \mu_i D_i + v_{it} \quad (2)$$

In the case of Random Effects, which can be used in cases were N individuals are drawn from a large population randomly, the following apply:

$$\mu_i \sim IID\left(0, \sigma_\mu^2\right), v_{it} \sim IID\left(0, \sigma_v^2\right) \tag{3}$$

with the $\mu_i s$ being independent of the v_{it}s, as are the $X_{it}s$ of the $\mu_i s$ and $v_{it}s$ for all I and t [40]. Inconsistency is checked in the RE estimate with Hausman tests, which determine whether the FE or RE model should be used.

In addition, Generalized Method of Moments (GMM) is used, in terms of orthogonal deviations, in order to capture the models' dynamic nature. As Arellano and Bond have stated [41], in orthogonal deviations, each observation is indicated as a deviation from the average of the sample's future observations. Each deviation is weighted to standardize the variance:

$$x_{it}^* = \left[x_{it} - \left(x_{i(t+1)} + \ldots + x_{iT}\right)/(T-t)\right]\sqrt{(T-t)}/\sqrt{T-t+1}, t = 1, \ldots T-1 \tag{4}$$

The $(Ti - q)$ equations for individual units i are:

$$Y_i = \delta w_i + d_i \eta_i + v_i \tag{5}$$

where δ is a parameter vector that includes αk, β, and λ, w_i is a data matrix that includes the endogenous variables' time series, the interpretive variables x and the time dummies, and d_i is a $(T_i - q) \times 1$ vector of ones.

Various problems might occur in panel data analyses; this is why several econometric tests are performed before the regression analysis. One of these problems is the correlation of the variables in the dataset. Pesaran's cross-section dependence test allows us to check if the timeseries are cross-sectional independent. In cases of cross-sectional dependence, OLS Dummy estimator (FEM) allowing for individual fixed effects with Driscoll-Kraay standard errors (in Fixed Effects models) can correct the variance–covariance matrix while, in Random Effects models, Breusch-Pagan LM test for individual effects and robust standard errors are applied.

Unit root tests are also performed, in cases where cross-section dependence is confirmed. Dickey-Fuller and Augmented Dickey-Fuller tests can be performed in panel data, with the issue of homogeneity in the autoregressive parameter. In addition, Westerlund tests are performed for panel cointegration, based on the significance of the error correction term in the error correction model. Four tests that check for panel cointegration are proposed: the Gt and Ga statistics, testing for the null hypothesis of no cointegration of all cross-sectional units. The rejection of the hypothesis implies cointegration for at least one unit. The Pt and Pa statistics also test the null hypothesis of no cointegration and their rejection implies cointegration for the panel in total [26,37–39].

4. Results

The descriptive statistics of the indicators used in the analysis (Section 3), are presented in this section. The highest percentages of people that were unable to keep their home adequately warm were observed in Bulgaria for various years, while high percentages were also observed in Portugal as well. The lowest percentages were found in Luxembourg and Norway. Greece presented the highest percentages of people facing arrears on utility bills, while high percentages were also found in Bulgaria. In contrast, the lowest percentages were found in Luxembourg and the Netherlands. Poland presented the highest percentages of people living in dwellings with leak, damp, or rot, while high percentages were also observed in Latvia and Cyprus. The lowest percentages were found in Finland for most years.

GDP per capita was also included in the analysis, expressed in purchasing power standards. The highest levels of GDP per capita were found in Luxembourg for most years, while the lowest levels were observed in Bulgaria. In addition, the highest levels of fossil fuels final energy consumption in households per capita were found in Luxembourg for most years, while the lowest levels were found in Iceland. Similarly, the highest levels of renewables and biofuels final energy consumption in households per capita were found in Latvia, while zero levels were observed in Malta for various years.

Table 2 presents the descriptive statistics of the variables used in our analysis.

Table 2. Descriptive Statistics of used indicators.

	Inadeq_Warm	Arrears	Leak_Damp	GDPpc	FFpc	RESpc
Mean	10.963	9.396	16.354	27,632.14	238.47	115.8
Median	5.9	6.9	15	26,400	205.16	96.833
Maximum	69.5	42.2	43.9	81,000	971.028	375.7
Minimum	0.3	1.1	4.1	7500	6.0576	0
Std. Dev.	12.403	7.58	7.577	11,602.94	194.8	86.498
Skewness	2.14	1.79	0.845	1.7245	1.0195	0.737
Kurtosis	8.557	6.23	3.687	7.679	3.8215	2.693
Jarque-Bera	918.9	433.76	62.12	630.73	90.21	42.33
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	448	448	448	448	448	448

To check for cross-section dependence, a Pesaran test is performed. All results reject the null hypothesis, indicating the existence of cross-section dependence, suggesting thus, the use of Driscoll-Kraay standard errors for the static regression models, in order to correct the variance–covariance matrix (Table 3).

Table 3. Pesaran CD test for cross-section dependence.

Variables	CD Test	*p*-Value
Inadeq_warm	12.751 ***	0.0000
Arrears	19.991 ***	0.0000
Leak_damp	5.754 ***	0.0000
GDPpc	60.94 ***	0.0000
FFpc	40.487 ***	0.0000
RESpc	26.142 ***	0.0000

Note: The null hypothesis assumes that there exists no cross-section dependence (correlation). Significance at *** 1%.

Fisher-ADF and Fisher-PP unit root tests are performed, which suggest that the examined variables are I(1), with stationarity evidence in first differences (Table 4).

Westerlund tests are performed to test for panel cointegration. The results suggest that the Gt and Ga statistics reject the null hypothesis in most cases, implying cointegration for at least one unit. In addition, the Pt and Pa statistics reject the null hypothesis in every case, implying cointegration for the whole panel (Table 5).

Six regression models were formulated, where each one of the three main variables that are considered to be core elements of energy poverty are used as dependent variables. In the static models, fixed effects model specifications are used, based on the results of the Hausman tests, with FE Driscoll-Kraay standard errors, based on the results of the Pesaran CD tests.

The results indicate that GDP per capita is negatively linked to each one of the three studied variables, in both static and dynamic models. This confirms the fact that economic growth can improve the conditions of energy poverty, since an increase in GDP per capita would lead to a decrease in the percentages of energy poverty factors, as well as that a financial crisis can significantly impact energy poverty conditions. These findings can be supported by other similar studies in the literature [26,27].

Table 4. Fisher-ADF and Fisher-PP panel unit root tests.

Variables	Fisher–ADF	Fisher–PP		Fisher–ADF	Fisher–PP
Levels			*First Differences*		
Inadeq_warm	61.786 [0.2771]	66.4179 [0.1608]	Inadeq_warm	125.574 *** [0.0000]	271.546 *** [0.0000]
Arrears	65.861 [0.1725]	47.145 [0.7943]	Arrears	131.534 *** [0.0000]	241.14 *** [0.0000]
Leak_damp	63.8516 [0.2200]	94.0092 *** [0.0011]	Leak_damp	196.915 *** [0.0000]	386.798 *** [0.0000]
GDPpc	27.4452 [0.9995]	43.196 [0.8948]	GDPpc	142.446 *** [0.0000]	216.594 *** [0.0000]
FFpc	60.7524 [0.3087]	90.7817 *** [0.0023]	FFpc	225.9 *** [0.0000]	484.769 *** [0.0000]
RESpc	47.635 [0.7793]	68.6455 [0.1196]	RESpc	139.17 *** [0.0000]	309.252 *** [0.0000]

Note: The null hypothesis assumes that the variable contains unit root. *p*-values in brackets. Significance at *** 1%.

Table 5. Westerlund Panel Cointegration Test.

Equation	Gt	Ga	Pt	Pa
Inadeq_warm = f(FFpc)	−4.87 *** [0.000]	−16.995 *** [0.000]	−25.779 *** [0.000]	−17.266 *** [0.000]
Inadeq_warm = f(RESpc)	−5.714 *** [0.000]	−20.715 *** [0.000]	−27.642 *** [0.000]	−24.629 *** [0.000]
Inadeq_warm = f(GDPpc)	−4.574 *** [0.000]	−15.71 * [0.099]	−19.278 *** [0.000]	−13.574 *** [0.000]
Arrears = f(FFpc)	−4.471 *** [0.000]	−14.028 *** [0.045]	−18.203 *** [0.000]	−15.061 *** [0.000]
Arrears = f(RESpc)	−5.028 *** [0.000]	−14.205 * [0.099]	−17.998 *** [0.000]	−14.687 *** [0.000]
Arrears = f(GDPpc)	−4.641 *** [0.000]	−15.478 * [0.099]	−21.56 *** [0.000]	−13.543 *** [0.000]
Leak_damp = f(FFpc)	−5.687 *** [0.000]	−20.236 *** [0.000]	−26.58 *** [0.000]	−18.585 *** [0.000]
Leak_damp = f(RESpc)	−5.766 *** [0.000]	−22.65 *** [0.000]	−29.639 *** [0.000]	−22.599 *** [0.000]
Leak_damp = f(GDPpc)	−5.12 *** [0.000]	−18.999 *** [0.000]	−20.253 *** [0.000]	−15.225 *** [0.000]

Note: The null hypothesis assumes no cointegration. Significance at *** 1%.

Fossil fuels final energy consumption in households per capita is inversely linked in both static and dynamic models to two out of the three indicators, indicating that an increase in the consumption of energy derived from fossil fuels can improve energy poverty conditions. Thus, it is proven that the increased use of fossil fuels per capita, which implies higher energy consumption, leads to better conditions regarding energy poverty in households. In the case of inability to keep the home adequately warm, the static model also indicates that the use of fossil fuels in energy consumption can improve these conditions; in contrast, the dynamic model indicates the opposite, implying a static rather than a dynamic influence of fossil fuels usage in such analyses.

Renewables and biofuels final energy consumption in households per capita is found to be a driver of arrears on utility bills, indicating that in the studied time period, higher levels of renewables' use led to difficulties in paying utility bills on time. These findings can also be supported by studies in the literature, where it has been argued that sometimes the costs to support renewables' technologies are transferred to consumers [28], leading therefore to higher electricity prices [26] and explaining, thus, the existence of arrears on utility bills.

In contrast, energy consumption produced from renewables is linked to an inverse relationship to the presence of leaks, damp, and rot in dwellings, according to both static and dynamic model. This indicates that an increase in renewable energy consumption per capita can improve these conditions in households. At the same time, a similar relationship is observed between renewable energy consumption and inability to keep the home adequately warm, according to the dynamic model, indicating that higher levels of renewable energy consumption per capita, would improve people's ability to keep their houses adequately warm. In the static model, renewables final energy consumption in households per capita is statistically insignificant (Table 6).

Table 6. Regression results with three different dependent variables.

	Inadeq_Warm		**Arrears**		**Leak_Damp**	
	FE (DK se)	**GMM**	**FE (DK se)**	**GMM**	**FE (DK se)**	**GMM**
Inadeq_warm(−1)		0.75999 *** (201.1128) [0.0000]				
Arrears(−1)				0.65311 *** (57.39698) [0.0000]		
Leak_damp(−1)						0.540377 *** (45.38322) [0.0000]
GDPpc	−0.000631 *** (−6.49) [0.000]	−0.000301 *** (−29.82716) [0.0000]	−0.000448 *** (−12.98) [0.0000]	−0.000334 *** (−18.0119) [0.0000]	−0.00042 *** (−3.26) [0.0050]	−0.000247 *** (−15.03851) [0.0000]
FFpc	−0.03163 *** (−6.38) [0.000]	0.014221 *** (30.87217) [0.0000]	−0.031625 *** (−7.68) [0.0000]	−0.018242 *** (−11.9915) [0.0000]	−0.023136 ** (−2.12) [0.0510]	−0.002276 * (−1.571195) [0.0970]
RESpc		−0.007889 ** (−2.468542) [0.0140]	0.02129 *** (3.03) [0.0080]	0.027379 *** (12.64376) [0.0000]	−0.02104 ** (−2.21) [0.0430]	−0.025261 *** (−19.58525) [0.0000]
Hausman	5.62 * [0.0601]		14.95 *** [0.0019]		19.16 *** [0.0003]	
Wald test		4867.066 (3)		4120.7 (3)		1269.12 (3)
Sargan test		26.5036 (25)		26.9428 (24)		26.4522 (24)
AR(1)		−2.2241 ** [0.0261]		−3.3234 *** [0.0009]		−2.1069 ** [0.0351]
AR(2)		0.3327 [0.7393]		−0.8542 [0.3930]		0.8247 [0.4095]
Observations	448	392	448	392	448	392

Note: t-Statistics in parentheses and *p*-values in square brackets. Parentheses in Wald and Sargan tests indicate degrees of freedom. Critical values for the Wald test of overall significance of the explanatory variables: $\chi_{20\cdot05,3}$ = 7.815. Critical values for the Sargan test for over-identifying restrictions: $\chi_{20\cdot05,24}$ = 36.415, $\chi_{20\cdot05,25}$ = 37.652. Significance at *** 1%, ** 5% and * 10%.

The lag of the dependent variables in the dynamic models are autoregressive-distributed lag specifications, that end up as an AD (1,0) formulation, showing the adjustment to equilibrium values. Table 7 presents the adjustment coefficients of each dynamic model, the discrepancy that is eliminated in a year between the actual and desired values and the periods that are required for the adjustment.

Table 7. Adjustment to equilibrium values, based on the lag in the dynamic models.

Dependent Variable	Adjustment Coefficient	Discrepancy between the Actual and Desired Values Eliminated in a Year	Periods Required for the Adjustment
Inadeq_warm	1–0.76	24%	More than 4 periods
Arrears	1–0.65	35%	Less than 3 periods
Leak_damp	1–0.54	46%	Approx. 2 periods

Wald tests of joint significance, as well as Sargan tests of over-identifying restrictions, are asymptotically distributed as χ^2 variables. Sargan statistics imply evidence of serially uncorrelated errors, since the null hypothesis of over-identifying restrictions is not rejected. AR(1) and AR(2) tests for first and second order serial autocorrelation do not reject the hypothesis of no autocorrelation.

5. Case Studies: Sweden, Germany, and Greece

Three countries, with different socioeconomic and environmental conditions, were chosen and their policies and progress on energy transition as well as their energy poverty-related conditions are analyzed, compared, and discussed in this section. The chosen countries were Sweden, Germany, and Greece. The three European countries were selected due to their different characteristics and the different socioeconomic, environmental, climatic and energy conditions existing in each one of them.

Sweden is a country in Northern Europe that is characterized by its proactivity on environmental issues and its climate consensus [42]. The country has been characterized as a global leader when it comes to low-carbon economy and has followed a successful path towards energy transition [43]. Sweden's energy needs are covered mainly by hydropower and biomass and the country's geography with moving waters and a big percentage of forest coverage is assisting that, despite the cold climate that requires a high amount of energy for heating [44].

The Swedish energy policies, which aim to promote sustainability, are based on energy policies set by the EU. The EU targets refer to reducing energy consumption by 32.5%, to provide at least 32% of energy consumption from renewable sources and provide at least 14% of energy consumption in the transport sector from renewable sources. Specifically for the Swedish targets, the country has aimed to achieve by 2030, 50% more efficient energy consumption, compared to 2005. In addition, the country's goal is to cover 100% of its electricity needs from renewable energy sources, by 2040 [45].

Germany is a country in Central Europe and has a highly industrialized economy that has been promoting an ambitious plan of energy transition over the past years [46]. The country aims to promote an economy that is low carbon, sustainable, and energy efficient and has achieved a significant growth when it comes to renewable power generation capacity, actively promoting the transition to renewable energy [47].

Since 2010, Germany has initiated and promoted a plan for a more efficient energy system that is based mainly on renewable energy sources, called *Energiewende*. More specifically, *Energiewende*'s targets include the provision of 50% of electricity supply by renewable energy sources and coal's phase-out by 2038 [48]. Data shows that two thirds of Germany's power generation could be covered from renewables by 2030, while solar energy and wind energy could cover half of that proportion [47]. However, and despite the progress that has been made, the evidence shows that the country is struggling to meet its targets, mainly due to the uneven progress that exists across sectors and challenges, especially in transportation and heating. At the moment, Germany uses fossil fuels at a high degree to cover its energy needs and coal is the largest source of power generation, although it is planned to be phased out by 2038 [49].

Greece is a country in South-eastern Europe that is also implementing reforms in the energy sector in order to foster decarbonization and promote a just energy transition. More specifically, the country aims to achieve a reduction in its greenhouse gas emissions by more than 56%, by 2030 (compared to 2005 levels), aiming to achieve by 2050 a climate neutral economy. However, at the moment, fossil fuels are the primary energy supplier in the country [50].

As stated in the National Energy and Climate Plan 2021–2030, Greece aims to increase the share of renewables to 31% by 2030, in order to contribute to the achievement of the EU target, that aims to increase the share of renewables to at least 32% by 2030. In addition, the country aims to reduce the use of lignite that is used for power generation, and to shut down by 2028 the lignite-fired plants, while ensuring energy security and promoting energy efficiency [51].

From this evidence, it is obvious that Sweden is in the lead when it comes to energy transition policies and promotion, while Greece is comparatively slower in the process of decarbonization, promoting less ambitious policies. This can also be observed by the provided data. As seen in Figure 2, among the three studied countries, Sweden has the biggest share of renewable energy in gross final energy consumption, reaching 56.39% in 2019. The country has achieved the target of reaching 49% by 2020, towards Europe 2020 target, which aimed to increase the share of renewable energy in gross final energy consumption in the EU to 20% by 2020. In Greece, the share of renewable energy reached 19.68% in 2019, and the country has also achieved the target of reaching 18% by 2020. In Germany, the same share was estimated at 17.35% in 2019 and the country was very close in achieving the target of 18% by 2020 [52].

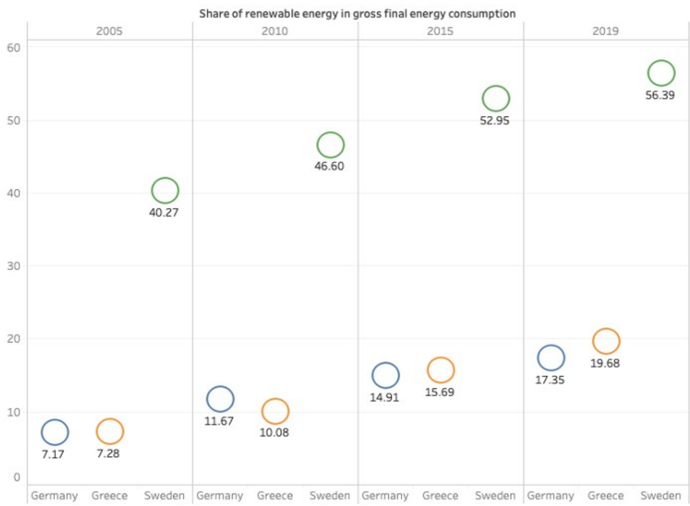

Figure 2. Share of renewable energy in gross final energy consumption in Sweden, Germany, and Greece (%).

The Energy Transition Index takes into consideration the performance of the current energy system as well as the enabling environment for energy transition and aims to reflect the relationships and dependencies that exist between the energy system transformation and various factors (economic, social, political, regulatory) that determine whether a country is ready for transition. According to the Energy Transition Index 2021, and as seen in Figure 3, Sweden is the global leader, ranking in the first place, while Germany is found in the 18th place and Greece in the 54th [53]. These rankings highlight once more the differences on energy transition potential and progress that exist among the selected countries and the necessity of efforts required to move towards sustainability in each one of them.

Figure 3. Energy Transition Index 2021.

After the comparative analysis of the energy transition progress and policies promoted in each one of the studied countries, an overview of the energy poverty situation and the policies regarding energy poverty is also presented. As seen in Figure 4, Greece was the country with the highest percentages of people living under energy poverty conditions among the three examined countries, according to Eurostat data. In contrast, low percentages were observed in Germany and Sweden for all three indicators; these countries perform better compared to the EU average on the specific indicators, while Greece has a significantly lower performance compared to the EU average.

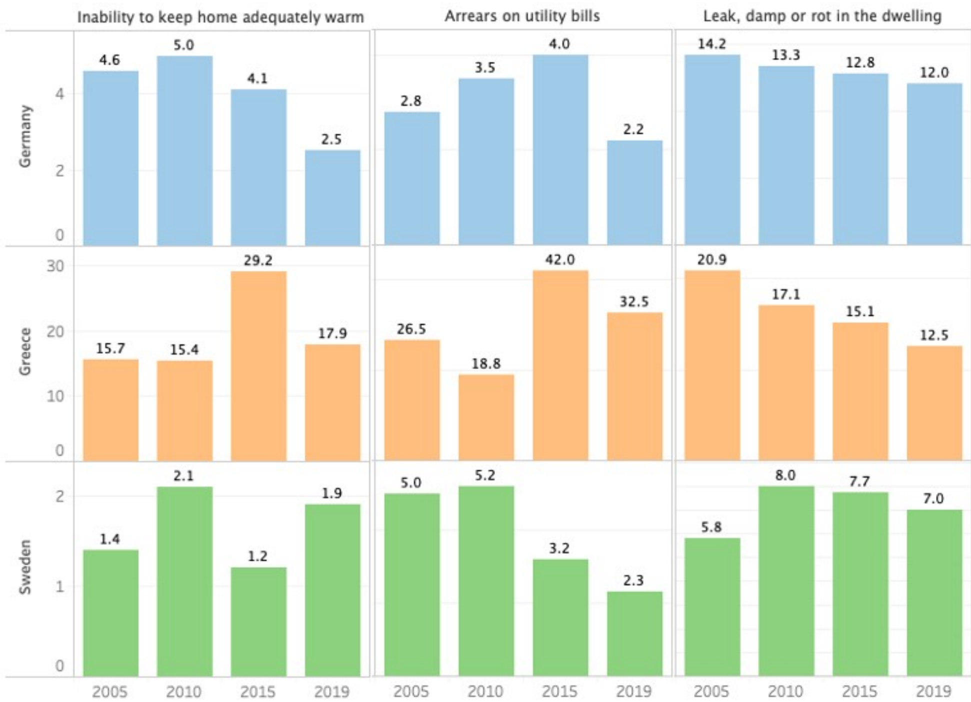

Figure 4. Data regarding inability to keep home adequately warm, arrears on utility bills, and presence of leak, damp or rot in the dwelling for Germany, Greece, and Sweden (% of population).

The data presented here for the three selected countries can also be compared to the findings from the analysis presented in Section 4. More specifically, we have found that an increasing GDP per capita can improve energy poverty conditions and, if we look closely at the data of the selected countries, we can see that in periods when GDP per capita was increasing in the studied countries, energy poverty levels were lower. Similarly, the results regarding the effect of renewable energy consumption per capita can also be validated, since we can observe that in most periods of higher levels of renewables final energy consumption in households per capita, higher percentages of households facing arrears on utility bills were also observed. However, it is important to further research each country's social, economic, and environmental conditions and active policies, in order to better understand the differences in energy poverty conditions and promote targeted and more effective policies and strategies.

According to the EU Energy Poverty Observatory, both Germany [54] and Greece [55] have an active research community, concerning the field of energy poverty, while the research in Sweden does not specifically focus on energy poverty, but on other energy-related fields, such as energy transition and efficiency [56].

Based on this evidence, it can be observed that Greece and Germany have developed and promoted various policies to lower energy poverty levels, while Sweden has not been actively addressing the problem, due to the already low levels that are observed in the country. Instead, Sweden is focusing on energy transition and renewable energy sources and has set ambitious goals. Germany and Greece have also been promoting energy transition policies, but their energy needs are still mainly covered by fossil fuels.

6. Conclusions

At the moment, the world depends highly on fossil fuels, despite their disadvantages and their impact on the environment. Energy transition and the use of renewable energy sources has been promoted a lot more in the past few years and a lot of countries have made significant progress to that end. However, the impact that energy transition and the use of renewable sources could have on the problem of energy poverty should be continuously studied and addressed.

This study contributes to the existing literature and expands the knowledge on the topic, focusing on assessing the impact that fossil fuels and renewables usage had on energy poverty conditions in 28 European countries during the time period 2004–2019. The necessary data were extracted from the Eurostat database and an in-depth econometric methodology was followed which, to the best of our knowledge, has not been used in similar studies. The findings suggest that GDP per capita and fossil fuels final energy consumption in households per capita are linked to an inverse relationship to energy poverty conditions. In addition, the results indicate that an increase in renewables and biofuels final energy consumption in households per capita led to an increase in the percentage of people facing arrears on utility bills, while it led to a decrease in the percentage of people that cannot keep their home adequately warm, and of the percentage of population living in a dwelling with a leaking roof, damp walls, floors or foundation, or rot in window frames or floor.

These results highlight the fact that higher fossil fuels usage per capita can improve energy poverty conditions, while also highlighting the assistance that a higher level of renewables usage per capita can provide in certain energy poverty conditions. Attention should be given, though, on the mitigation of the impact that renewables' usage can have on arrears on utility bills. Government and policy makers should be aware of this relationship and develop strategies that promote energy transition while protecting energy consumers. More specifically, there should be given extra attention in not transferring the costs of renewables to consumers [28] and in promoting policies that assist households pay their bills on time, while also ensuring that the mitigation of fossil fuels usage will not have an impact on system's stability [12], leading to other social or economic problems.

Additionally, three case studies were examined and the conditions in three European countries with different socioeconomic and environmental characteristics (Sweden, Germany, and Greece) were presented and compared. The evidence shows that Germany and Greece have focused on energy poverty mitigation while Sweden, which manages to keep its energy poverty levels significantly low, promotes more ambitious strategies regarding energy transition. Between the examined countries, Greece is the one with the highest energy poverty levels while Sweden is the one with the highest share of renewable energy in gross final energy consumption.

This comparison can be useful for policy makers, since it highlights the differences that exist among European countries in these fields and the importance to promote and implement targeted policies in each country, based on their progress and needs. Outside Europe, and when it comes to developing countries, policy makers should take into consideration other studies in the literature to support effective renewable energy development, focusing on market guarantee, lowering the costs of licensing for renewable projects, raising public consciousness, and increasing R&D, among others [57]. In general, the role that cities and communities play in ecological and energy transition should be examined and taken into consideration by policy makers, when promoting relevant strategies [58], while it would also be useful to explore the impact that subsidies towards green resources can have in supporting energy transition [59] and, subsequently, how these could impact energy poverty conditions in certain countries and regions. Finally, the impact of the COVID-19 pandemic on environmental matters and on renewable energy should be taken into consideration when promoting strategies for specific countries or regions, assessing the impact that the pandemic had on energy markets [60].

While the results of this study highlight the linkages that exist between energy coming from different sources and energy poverty conditions and can be proven helpful for governments and policy makers, future research on this relationship is strongly suggested. More specifically, extensive research targeted to specific countries or regions is essential, examining not only the current situation and the current linkages, but also the tailored policies and strategies that should be promoted for achieving a successful energy transition while ensuring energy security, minimizing energy poverty levels, and progressing on the targets of the 7th Sustainable Development Goal at the same time.

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Determinants of Renewable Energy Consumption in Africa: Evidence from System GMM

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Abstract: The adoption of renewable energy remains Sub-Saharan Africa's best option to achieve sustainable growth and mitigate climate change. The essence of this study is to examine the factors that determine the adoption of renewable energy adoption in Africa by employing the System Generalized Methods-Of-Moment (GMM) to analyze data sourced from 1990 to 2019 on some selected African economies. The study examined the tripartite role of the economic, environmental, and socio-political factors on renewable energy adoption in Africa and noted that a positive relationship exists between economic and renewable energy adoption, supporting the validity of the feedback hypothesis. Hence, a policy that supports simultaneous growth of the economy and renewable energy could be adopted. The results further show that environmental factors such as carbon emission and ecological footprint negatively impact renewable energy (RE) adoption in Sub-Saharan African economies. The impact of socio-political factors is, at best mixed; for instance, the result of urbanization is positive and significant, suggesting that urbanization helps in the quick adoption of renewable energy in the studied economies, while the results of corruption show otherwise. To account for single-country dynamics, the study employed the full PMG and noted that the pollution haven hypothesis holds for a number of African economies. The results offer some policy implications.

Keywords: renewable energy; climate change; carbon emission; economic growth; Africa

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1. Introduction

Top on the agenda of global policymakers is defining and designing suitable energy, economic, and environmental policies that can mitigate increasing global carbon dioxide emissions (CO_2) [1–5]. This is premised on the fact that increasing CO_2 emission negatively impacts human wellbeing and health and poses a threat to handing over a secure and sustainable environment to the future generation [6,7]. Achieving sustainable environmental policies capable of reducing CO_2 emissions requires a comprehensive and robust understanding of its causes [8–13]. Extant literature suggests that to keep humanity and prevent negative alteration of man's state; concerted efforts must be taken to reduce and mitigate the impact of greenhouse gas (GHG) emissions and keep the average global temperature at the pre-industrial state of less than 2° C (IPCC 2007, Kyoto Protocol 1997) [4,14–16].

Evidence such as continuous occurrences of super droughts, wildfires, and hurricanes, among others that suggest the intensification of extreme weather events and natural disasters occurring in higher numbers or frequencies as well as magnitude across the globe call for urgent attention from governmental and non-governmental organizations, bilateral and multilateral institutions, to mitigate climate change/CO_2 to avert global disaster [4,5,17,18]. Several actions and policies have been canvassed by various international institutions to curb the negative impact of CO_2 emissions over the years [19–21]. Some of these policies often center on improving energy efficiency, conserving energy, and designing energy strategies [22]. The main drivers of these policies are reducing the high levels of CO_2 emission from intense nonrenewable energy sources and reducing the high percentage of nonrenewable energy in the total energy component (nonrenewable accounts for more than

80% of the global total energy components). At the center of these two policies is the need to increase the world component of renewable energy in the global energy mix.

Over the past decades, advocacy has identified renewable energy (RE) sources as reliable alternative sources of energy to conventional fossil energy sources such as crude oil, coal, and natural gas, stressing that they have some added advantages of being environmental-friendly, readily available, among others [23]. As noted by [22], there is a rapid decline in the generation cost of renewable energy. There has been strong advocacy for its usage by international organizations such as the 1997 Kyoto Protocol, the 2016 Paris agreement (COP21), the International Energy Agency, and the United Nations, just to mention a few, as it is environmentally friendly and possess the ability to mitigate climate change, produces either no or minimal global warming emissions [24,25]. Essentially, RE promotes economic growth in a number of ways. (i.) RE technologies support the diversification of the energy mix and support energy security via the provision of a reliable, vast supply of renewable energy necessary to achieve sustainable economic growth. (ii.) RE advances both social and environmental benefits as it reduces the amount of CO_2 emission into the environment, hence reducing the cost of addressing environmental pollution. (iii.) Developing RE sources assist economies in becoming self-reliant for energy and avoiding energy shortages arising from external shocks. (iv.) RE creates job opportunities, among others. It is also worth noting that the continuous shocks or upsurge in oil prices and prices of other fossil fuels against the continuous fall in RE technologies are incentives to shifts towards RE sources adoption [26].

Despite the strength of RE as a source of energy, its universal adoption has been relatively slow. For instance, 80% of the world's energy mix is still comprised of nonrenewable energy. This will have a negative effect on the effort to switch toward a green and sustainable energy system. Hence there is a need to explore the drivers of the deployment of RE to know what factors maximize the achievement of sustainable energy. According to [27], factors that can influence the adaption of RE can be classified into nine strands: political, institutional, economic, social, environmental, regulatory, technical, technological, and logistics.

Extant literature on the determinants of RE adoption is multi-dimensional, focusing on energy indicators, environmental factors, explanatory variables, regions and countries, time periods, econometric models, and estimation techniques [27]; for instance, [8,28–31]. In terms of the methodology adopted, ref. [32] canvassed for strong modeling techniques, ref. [33] employed panel data estimation techniques, ref. [34] employed panel autoregressive distributed lag (P-ARDL), and ref. [35] employed bootstrap ARDL, among others. A closer look at most of the extant studies suggests that though Africa has a huge reserve of renewable energy, few studies have been conducted on the possibility of switching toward the adoption of renewable energy. There are few appreciable studies on the determinants of drivers of RE adoption on the continent. This, among others, is the essence of the current study.

A major factor in mitigating increased emission rates is adopting RE in the production and consumption life. RE is healthy for public health, the environment, and the economy; hence, focusing on adopting RE is key to achieving environmentally sustainable economic growth. RE, among others, helps in diversifying the energy mix, increases energy security as it provides a reliable, vast, and renewable supply of energy needed for sustainable growth, and reduces environmental costs owing to addressing issues related to CO_2 emissions. Specifically, RE can be influenced by three main constructs: economic, environmental, and socio-political factors [36–38]. The impact of economic growth on RE adoption could be explained by the influence of macroeconomic variables such as real gross domestic product (RGDP), foreign direct investment (FDI), financial development (FD), and trade openness (TRD), among others. Similar to every source of energy, four possibilities exist in explaining the linkages between economic growth and RE. They are RE-leading, economic growth following hypothesis; economic growth leading, RE following hypothesis; feedback hypothesis where a bilateral relationship exists between RE and economic growth; the fourth possibility is the neutrality hypothesis, where no causality exists between economic growth and RE [20,39,40].

The impact of environmental factors on RE adoption is essentially influenced by two models: the environmental Kuznets hypothesis (EKC); and the pollutant haven models. The EKC noted that a U-shape relationship exists between economic growth and environmental pollution. The theory simply described a non-linear relationship between growth and environmental degradation. The pollutant haven model stressed that the existence of legislation to punish the deployment of environmentally harmful energy sources would motivate the adoption of RE [41–43].

The socio-political strands focus on the ability of governance structure, government policies, and urbanization, among others, to influence the adoption of RE [44–46]. Urbanization as a socioeconomic factor impacts energy consumption and environmental condition as it may induce the enlargement of energy-intensive industries such as steel and concrete, the power industry, and the transport sector, thereby provoking upward shocks to the environment [47]. Another dimension to the contributions of urbanization to energy consumption and the environment suggests that urbanization might improve the environmental quality, provided man is willing to be environmentally conscious and friendly. As important as these constructs are to the adoption of RE, few studies have accounted for them in RE adoption works. For instance, refs. [1,2] did not account for the impact of socio-political factors, and [48–51] only focused on environmental factors. Refs. [52–54] focused on both economic and environment but did not address socio-political factors. The crux of the current study is to calibrate these constructs to discuss RE adoption with a focus on Africa.

Several factors induced our motivation on Africa (as of 2017, African CO_2 emission was 4% of global CO_2 emissions. It grew at an average of 4.6% yr^{-1} over the period 1990–2017 against the global rate of 12.2% yr^{-1}); for instance, extant studies and reports have noted the deteriorating nature of the environmental space in Africa over the last few decades [55,56]. Air pollution and CO_2 emissions account for environmental degradation in the region more than other types of pollution, such as water or land pollution. The region is reported to have one of the most prolonged CO_2 emission growth rates in the world, with more than a 123% growth rate between 1979 and 2017, surpassing the global average of 60% [57,58]. With the current trend in CO_2 emission growth rate, Africa will, by the year 2030, have a 30% CO_2 emission growth rate.

The essence of this study is to investigate the nexus between RE and economic growth, the environment, and socio-political factors by employing a System Generalized Methods-Of-Moment (GMM) model. Our choice of system GMM was influenced by its many advantages over alternative estimation techniques, such as the difference GMM. For instance, system GMM has three clear-cut advantages: (i.) It is useful in reducing endogeneity bias; (ii.) it reduces time-varying measurement error bias; (iii.) it reduces weak instrument error bias [20,59,60]. The system GMM helps address the issues related to endogeneity resulting from the inclusion of other potential endogenous explanatory variables, as well as other possibilities of measurement errors owing to the use of cross-country data displaying high persistence [61–65]. The study intends to ask the following research questions: (i) What drives renewable energy adoption in Africa? (ii) To what extent do macroeconomic variables impact renewable energy adoption in Africa? (iii) Do environmental factors impact renewable energy adoption in Africa? (iv) What is the role of socio-political factors in renewable energy adoption in Africa?

Our study's novel contribution to literature is four-fold. First, to the best of our knowledge, we are among the first studies to examine the drivers of RE consumption in Africa. Africa, as a growing economy, is in dire need of energy and is simultaneously faced with the need to have a safe environment given the alarming rate of CO_2 emission of 123%, surpassing the global average of 60%. Therefore, Africa needs to switch from traditional fossil fuel-dominated energy sources to clean and safer RE sources; hence the need to understand the drivers of RE adoption for appropriate policy adjustment. Secondly, we account for the role of macroeconomic variables, environmental constructs, and socio-political factors in the nexus between energy, economics, and the environment. Thirdly, we employed novel and appropriate estimation techniques, the system GMM which is useful in reducing endogeneity bias, time-varying measurement error bias, and weak instrument error bias, and reducing measurement errors owing to the adoption of cross-country data. Fourthly, we offer some policy implications.

Our study will provide insights into at least six Sustainable Development Goals (SDGs): SDG 7- affordable and clean energy; SDG 8- economic growth; SDG 11- sustainable cities and communities; SDG 12- responsible consumption and production; SDG13- climate action; and SDG 17- partnership for the goal with trade offering leadership.

The remainder of this study is as follows: Section 2 presents the literature review; Section 3 presents the materials and estimation techniques; Section 4 deals with the presentation and discussion of results, while Section 5 concludes the paper.

2. Literature Review

The theoretical note that governs this study is threefold: cointegration (economic growth-related), environmental, and impact. The cointegration (economic growth) strands are further divided into four hypotheses that explain the possibility of causality between RE and economic growth. These hypotheses are energy-leading growth following hypothesis, which states that it is the demand for energy that spurs economic growth; hence, conservative measures to conserve the environment will have negative consequences on economic growth. The second leg of this strand is the economic growth-leading following hypothesis that suggests that it is growth that drives energy demand. The third strand is the feedback hypothesis which states that a bilateral relationship exists between economic growth and energy consumption. The fourth hypothesis is the neutrality hypothesis which suggests that no causality exists between economic growth and energy consumption. Hence, any policy introduced to manipulate either of the two will have little or no effect on the other [20,66,67].

The discussion of the extant literature on the impact of macroeconomic variables on energy behavior remains inconclusive; for instance, ref. [2] examined the dynamic effect of nonrenewable energy, renewable energy, economic growth, and foreign direct investment on the environment based on data sourced from the year 2000 to 2015 for some selected African economies. The study employed panel ARDL that calibrates the pooled mean group, mean group, and dynamic fixed effect estimator to examine the validity of both the environmental Kuznets curve and/or pollution haven hypothesis. The result attained shows that while a negative and significant relationship exists between renewable energy and CO_2 emissions, the relationship between CO_2 and other explanatory variables is positive and significant, both in the short and long runs, except for FDI, which is positive only in the long run. The study noted that EKC does not hold for the studied economy; as a result, it tilts towards the pollution haven hypothesis. This suggests that African economies are less concerned about their environment but place a high premium on growth. A major difference between ref. [2] and the current study is the fact that whereas the former does not discuss socio-political factors, the latter calibrated it into their model; the current study accounts for single-country analysis.

For some selected 55 economies, ref. [68] employed a two-system GMM procedure to examine the nexus between financial development and renewable energy adoption based on data sourced from 2005 to 2014. The study noted that a positive and significant relationship exists between financial development and renewable energy for high-income economies though the relationship is insignificant for low-income economies. The study noted that sophisticated financing is key to achieving RE in the studied economies. The study also noted that the impact of trade openness and carbon emission are statistically insignificant for the economies studied, suggesting that trade has no impact on RE adoption. The results from the impact of carbon emission on RE adoption are intriguing, especially for high-income economies. The authors concluded that the EKC model is valid for the studied economies.

In a related development, ref. [69] noted that financial development is key to achieving the adoption of RE in China. The study emphasized the role of green financing and a green reputation in achieving the deployment of renewable energy that will support growth. The study employed several econometric techniques to analyze both micro and macro data on the Chinese economy from 2015 to 2020. The study identified oil price volatility and geopolitical risk as key obstacles to adopting RE in China. In a related development, ref. [70] noted that financial development is key to achieving RE consumption in Africa based on the study estimation of the generated method of moments (GMM) and quantitative regression (QR) in analyzing data sourced from 2004 to 2014. The study noted that financial inequality is a major setback to progress in RE consumption in Africa.

Ref. [71] noted that financial development, agriculture, and economic growth are key to the adoption of RE in Africa, while corruption and bad governance negatively affects Africa's adoption of RE. The study analyzed case studies, research articles, policy briefs, and project reports across and beyond Africa. It noted that for Africa to achieve the SGDs, the operations of Power Africa, Sustainable Energy for All (SE4ALL) initiative, concerted efforts must be put in place to address corruption on the continent.

Ref. [72] noted that FDI negatively impacts the environment on the one hand and RE consumption on the other hand for China based on the results obtained on the deployment of systems GMM, random effect, and fixed effect on the annual date from 2011 to 2016. The study noted that the pollution haven hypothesis is valid for the study economy.

Ref. [73] noted that RE and nonrenewable energy (N-RE) are key determinants of FDI inflows. Trade, tourism, and market size play positive but less significant roles in attracting FDI for the BRICS, stressing that a negative relationship exists between FDI and inflation rate. Ref. [74] noted that RE has a neutral effect on FDI. Instead, the institutional environment and land availability are the core factors that stimulate FDI. Ref. [75] noted that a long-run relationship exists between FDI, RE, and economic growth for some selected nine countries identified in the Climate Change Performance Index 2018 report

Ref. [76] estimation of data from G-C economies based on data sourced from 1978 to 2014 shows that capital market expansion and trade openness are the leading drivers of CO_2 emission. The results further noted that CO_2 is respectively related to RE adoption (see also ref. [77]. Their results tilt toward the pollution haven hypothesis

In agriculture, ref. [78] shows that a long-run relationship exists between agricultural land expansion and CO_2 emission in Peru though RE improves environmental quality by reducing CO_2 emission. Ref. [79] noted that a positive relationship exists between agriculture and RE, but no such relationship is found to exist between agriculture and CO_2 for the economies of the US, Canada, China, and Poland. Ref. [80] noted that a bidirectional relationship exists between energy and agriculture for the EU. Ref. [81] noted that agriculture, RE, trade, and globalization negatively impact CO_2 emissions in Turkey. The study tilts toward the pollution haven hypothesis for Turkey.

The theoretical note from the environmental strands can be classified into two main types: The Environmental Kuznets Curve and the pollution haven hypotheses. The EKC opined that the relationship between economic growth and environmental pollution is in the form of an inverted U-shaped, such that at the early stage of a nation's economic growth, environmental pollution deepens, and after reaching a certain threshold level, environmental pollution begins to decline. The proponents of this hypothesis are of the view that at the initial stage of development, economies are concerned with achieving economic growth with less concern for protecting the environment, but with time and advancement in economic growth comes a surge in environmental pollution, and attention begins to shift towards achieving clean energy [41,42,82,83].

A variety of these models has been canvassed in the literature focusing on CO_2 emissions as indicators of environmental pollution [42,84]. Some have calibrated the ecological footprint [49,85]. Recent studies have calibrated macroeconomic and finance-related variables to the studies on EKC [86]. The discussion on the relevance of EKC is continuous and yet to be concluded.

The pollution haven hypothesis (PHH) is the view that multinational companies that engage in rigorous pollution fields prefer to move to developing countries with fewer environmental/ecological protection laws. The reverse of the pollution haven hypothesis is the pollution halo hypothesis, which states that FDI could induce a downward trend in CO_2 emission, hence promoting energy-efficient technology usage that revolved around sustainability methods. Accordingly, it is believed that FDI can positively impact the ecosystem of an economy in three channels: scale effect (economic size), technical effect (improved technology), and structural effect (improvement in manufacturing design). The interaction of these effects will improve growth and reduce CO_2 emissions. The proponent of this hypothesis has identified FDI and yawning for development as the key drivers of CO_2 emissions in developing economies [7,42,47]. Closeness to colonial masters by former colonies and globalization, among others, are the reasons that account for the movement of multinational firms with toxic production outlets to less developing economies [72].

The studies on the impact of ecological footprints suggest that a functional relationship exists between the ecological footprint and several variables. For instance, ref. [86] noted that financial debt and renewable energy help reduce environmental degradation and that financial debt, RE, and NRE positively impact the growth of the 15 highest emitting economies. Ref. [86] noted that economic growth and national resources advance the ecological footprint and that human capital in the current state cannot mitigate environmental deterioration. Though RE does decrease ecological footprint, the study established the existence of feedback causality between human capital, urbanization, and ecological footprint. Ref. [31] noted that RE decreases ecological footprint in the long run in Turkey and that a bi-directional relationship exists between RE and economic growth and ecological footprint.

The theoretical note on impact assessment focuses on the role of governance and other socio-political factors in shaping the choice of energy usage to achieve carbon neutrality. The proponents of this thought believe that climate change is a global public issue and requires effective climate governance to address it [87–90]. As noted by ref. [91], energy governance is key to decoupling carbon emissions as it is vital to promoting RE adoption. For a sample of 36 emerging economies, ref. [92] observed that good governance especially economic and institutional governance is key to mitigating CO_2 emission and progressive adoption of RE. Ref. [93] designed a novel, holistic analytical approach to examine energy access governance for the Southern African economies of Uganda and Zambia by employing three data collection methods: qualitative document analysis, semi-structured stakeholder interviews, and closed surveys. The study noted that the rule of law, transparency standards, accountability, and inclusiveness are key to accessing RE for the studied economies. The study also noted that competing regulatory frameworks distort access to RE. Ref. [90] cautioned on the danger of monopolized power in designing and implementing RE for the economies of Nepal and Indonesia. The authors noted that RE designed in the studied economies was bedeviled with the inability to carry the major stakeholders along in its design and running.

Ref. [94] calibrated the role of corruption perception and political governance in energy consumption-economic growth nexus for a team of 49 economies using a dynamic data environment analysis model based on data sourced from 2007 to 2016. The study noted that political governance proxied by political stability, bureaucratic quality, personal safety and security of private property, and legal and regulatory frameworks positively impact energy consumption.

Ref. [89] employed machine learning techniques to analyze the impact of green governance on renewable energy consumption in India and noted that governance structure influences the adoption of energy choices. The study further noted that the taxonomy of green governance proxy by global governance, adaptive governance, climate governance, ecological governance, self-governance, energy governance, and information technology governance are related and work on the same objectives by pursuing different activities.

For Switzerland, ref. [95] examined the role of public awareness and governance structure in the effective transition from nonrenewable energy consumption to renewable energy sources. The study noted that public awareness and good governance are crucial to the effective transition and adoption of RE (see also ref. [88]. Ref. [96] explored the role of both internal and external governance structures in the adoption of renewable energy for some selected 1027 firms spread across 47 economies/regions. The study noted that internal governance structure tends to have a negative influence on RE adoption as it often induces a declining influence on RE, whereas external governance has a negative impact.

In Brazil, ref. [97] employed quantitative measures to access the nexus between water, energy, food, and land as it affects the adoption of biofuels emanating from sugarcane. The study concluded that each of these factors is key to achieving sustainable/green energy adoption in the studied economy. A study by ref. [97] was further expanded by ref. [98], who calibrated the role of geopolitics in adopting RE in Mexico. The study employed an external multi-regional input-output model (EMRIO) that calibrates import dependence and governance quality into the RE adoption framework for the Mexican economy. The study noted that better governance is key to the successful adoption and implementation of RE in the studied economy.

Ref. [50] noted that for governance structure and effectiveness to influence the adoption of RE positively, there is a need to have a holistic view of the consequences of RE adoption by calibrating natural resources extortion into the equation. The study argued that evidence abounds to show that the transition from a fossil-dominated system towards RE will have negative consequences on metal by more than a fraction of 7 by 2050 when compared with the 2015 levels, especially in economies with weak, poor, and failing resource governance up to between 32 and 40%.

Ref. [99] noted that political interference in environmental management, poor or lack of effective implementation, and lack of political independence of environmental agencies, which increases the risk of consumption, are the main factors militating against the adoption of RE in Brazil (see also ref. [100]).

A critical look at the literature reviewed here suggests that little or no study has been conducted on the determinants of renewable energy consumption in Africa, and their findings are inconclusive. This is what the current study aims to do, and by extension, calibrate the role of environmental factors, economic growth, and socio-political factors to study RE adoption in Africa.

3. Materials and Methods

The section presents the data-generating set and sources. It also presents the methodology employed and the justification for employing it.

3.1. Data

The data for the current study were sourced from several reputable global data outlets. For instance, we obtained data on macroeconomic variables, including real gross domestic product (RGDP), foreign direct investment (FDI), financial development (FD), trade (TRD), and government spending (GOVT) from the World Development Indicators (various issues). The data on the inflation rate (INF) was sourced from the United Nations Statistics (UN Data). We sourced data on agricultural output (AGRIC) from the Economic Research Service of the US Department of Agriculture (USDA). Data on environmental factors proxy by CO_2 emission (thousand kt) and ecological footprint were sourced from the BP Statistical Review of the World Energy (various issues). To account for the impact of socio-political factors, we calibrated the impact of governance effectiveness (GOVE) and urbanization (URB) into our model. Data on these variables were sourced from the World Development Indicators (various issues). We also account for the impact of the life expectancy index, education index, and corruption perception index as part of our socio-political factors in shaping the adoption of RE. Data on the education index (EI) and life expectancy index (LEI) were sourced from the United Nations Development Program (UNDP) development reports (various issues). Meanwhile, data on the corruption perception index (COR) was sourced from the Transparency International database. To address issues relating to heteroscedasticity, we standardized our variables by obtaining their natural log forms. Data on renewable energy were sourced from the International Energy Agency database (various issues).

A Priori Expectations

Theoretically, we expect a positive relationship between RE and each RGDP, financial development, trade openness, agricultural output, and FDI. A negative relationship is expected to exist between RE and inflation. On environmental variables, we expect an inverse relationship between RE and CO_2. On socio-political constructs, we expect that a positive relationship should exist between government effectiveness and RE. The relationship between RE and urbanization could be either positive (if the people are en vironmentally conscious) or negative if smart cities and the environment are neglected. The relationship between RE and other variables could be either way.

3.2. Methodology

The essence of the current study is to examine the determinant of RE adoption in some selected African economies. The study explored the neoclassical production function employed by [20,26,101] to develop the model for the study as stated below:

$$RE_{it} = \alpha_1 RE_{it-1} + \beta_1 W_{it} + \beta_2 X_{it} + \beta_3 Z_{it} + \delta_t + \varnothing_i + \varepsilon_{it} \tag{1}$$

where RE_{it} is the renewable energy consumption per capita, W is the proxy of all macroeconomic variables that can influence renewable energy consumption, X is the proxy of all environmental factors that can influence renewable energy consumption, Z is the proxy of all socio-political factors that can influence renewable energy consumption, α *and* β are the coefficients of the model, $\varnothing_i$ is the time-invariant country effects, δ_t is the unobservable time effects, ε is the residual term, t is the time period. The GMM estimation techniques proposed by Arellano and Bond for our model, as stated in Equation (2), are as follows:

$$E(y_{it-s} - \Delta u_{it}) = 0 \; for \; t = 3, \ldots\ldots T \; and \; 2 \leq T \tag{2}$$

Here, y_{it-s} is the suitable lags of the dependent variables. The implication is that the second and further lags of the dependent variables are employed as an instrument for the residual of Equation (1) in differences. As noted by refs. [20,59,102], the estimator of Equation (2) is prone to a huge small sample bias, given the fact that the number of periods is small, with the dependent variables presenting a high degree of persistence. To address this, our study employed the system GMM model as suggested by refs. [40,101,103]. The model is as follows

$$E(\Delta d_{it-s} - (\delta_i - u_{it})) = 0 \; for \; t = 3, \ldots\ldots T \tag{3}$$

It becomes unattractive and inappropriate to employ the ordinary least squares (OLS), fixed effects, or random effects because of the presence of lagged endogenous variable $y, \; t-1$ in Equation (1), given that y_{it} is correlated with δ_i and it induces upward biases, which is inconsistent with the OLS assumption of independence of the error term from the regressors [101,104–107]. To address this problem, the extant literature on dynamic panel models employed the Arellano and Bond GMM estimation model that employs an internal mechanism to explore the correlation between $y, \; t-1.$ and δ_i. The GMM techniques remove $\varnothing_i$ in short dynamic panels such as Equation (1) by differencing it first. To obtain a relatively consistent estimator, we employed lagged values of the levels of the independent variables as the predetermined variables [26,108]. In specific, when $\varnothing_i$ (I = 1,2, ..., n) are serially uncorrelated, then the second and higher-order lags of the independent variables are valid instruments. Extant literature has shown that a major problem of the [104] GMM model is that it produces poor instruments for the regressors when the regressors display persistence over time. To overcome this challenge, Arellano and Bond 1995, developed a system GMM that can estimate two sets of equations: (i) A set of levels that employ lags of the regressors in first differences as instruments; (ii) a set of equations in first differences that employs lags of the regressors in level as instruments. From the narrative, it can be deduced that the system GMM is superior and appropriate for our model when compared with the difference GMM in at least three areas. (i.) It reduces endogeneity bias. (ii.) It reduces time-varying measurement error bias. (iii.) It reduces weak instrument error bias.

The current study employed the system GMM to address the endogeneity in the data generating set that could occur as a result of including $y,\ t-1$, an indication that RE consumption and many of the other regressors may be jointly determined by the growth rate of the GDP, as well as the possibility of measurement errors that could occur because of employing cross country data that displays high persistence. To examine the validity of the orthogonality assumption of system GMM, we employed the Hansen test of over-identification and the Arellano and Bond tests for second-order and higher-order several correlations $AR(2)$ test, given that system GMM techniques rely on internal instruments. The study adopted the [109] small sample correction of the standard errors for all the two-step system analyses, as suggested by ref. [110]. Some of the variables in some of the studied economies are heterogeneous; hence, we employed a full PMG method for the short-run nexus following [111–113].

4. Results and Discussion

We present the results of the current study in two parts. The first part focuses on the nexus between RE, economic growth, environmental factors, and socio-political factors in the selected African economies, based on system GMM estimation techniques. The second is our analysis focused on the country-specific output of these relationships in each studied economy.

4.1. System GMM Estimates

We present the descriptive analysis results of the relationship between the variables explored in Table 1. The results suggest that FDI has the lowest mean, while corruption has the highest mean value. The result, as presented by standard deviation, suggests that corruption has the highest standard deviation, while RGDP has the lowest standard deviation.

Table 1. Descriptive statistic.

Variables	Descriptive Analysis				Normality Analysis (Natural Log-Form)			
	Mean	Max.	Min.	SD	Skewness	Kurtosis	Jarque-Bera	Probability
InRE	1655.98	2368.77	1032.67	367.09	−0.98	2.04	4.77	0.06
InRGDP	0.59	0.88	0.04	0.51	−0.34	3.19	0.72	0.67
InFDI	46.44	64.07	34.57	5.12	0.55	2.04	3.53	0.16
InFD	1438.78	1968.09	1011.11	214.09	−0.56	3.05	478	0.07
InTRD	1.65	2.32	1.33	0.34	0.13	1.45	3.02	0.24
InGOVSD	2.86	5.01	1.18	0.44	0.04	1.63	2.16	0.25
InINF	2.11	5.11	1.15	0.24	0.03	1.43	2.13	0.15
InAGR	11.98	2.07	12.67	7.09	0.71	2.02	4.74	0.04
InC02	12.59	2.88	4.04	0.41	0.23	3.29	0.73	0.47
ECL	43.41	62.01	32.53	5.23	0.51	2.14	3.23	0.36
GOVE	1.78	1.99	1.21	4.49	0.36	3.11	112	0.05
InURB	1.62	2.12	1.31	0.31	0.14	1.15	3.01	0.21
LEI	2.11	3.11	1.12	0.14	0.15	1.03	2.13	0.23
EI	15.18	24.7	2.27	2.04	0.18	1.04	4.01	0.05
COR	0.44	0.14	0.14	0.31	0.31	3.14	0.32	0.17

Source: Author's computation 2023.

We present the results of the impact of our independent variables on the dependent variable (RE) in Table 2. From the results, as shown in columns (1–5), the results of the OLS, fixed effects, baseline system GMM, and alternative system estimates are presented respectively for robustness purposes. As earlier noted, OLS estimation of Equation (1) induces upward bias for the lagged per RE, while fixed effects induce a downward bias. Empirically, a valid estimate is expected to lie between the OLS and fixed effects [20,60,65,110]. Our results, as presented in column 3 of Table 2, suggests that the two-step system GMM coefficient on the lagged RE is −1.582, and it is between the upward-biased OLS estimates of

−1.143 and downward-biased fixed effect estimates of 5.446. The results also suggests that our estimation is negative and highly significant. This suggests the existence of conditional convergence across the selected African economies studied (See also [111]).

Table 2. Baseline system GMM results.

Dep. Variable: *RE*	[1] OLS	[2] Fixed Effect	[3] SYSGMM1	[4] SYSGMM2	[5] SYSGMM3
InRE	1.644	1.754	2.671	2.601	1.908
	[0.012]	[0.051]	[0.132]	[0.102]	[0.014]
InRGDP	0.169	0.167	0.176	0.164	0.161
	[0.012]	[0.004]	[0.004]	[0.006]	[0.023]
InFDI	0.015	0.017	0.019	0.014	0.298
	[0.015]	[0.051]	[0.002]	[0.004]	[0.013]
InFD	0.042	0.029	0.027	0.074	0.043
	[0.071]	[0.052]	[0.025]	[0.062]	[0.016]
InTRD	0.056	0.058	0.061	0.059	0.058
	[0.051]	[0.051]	[0.005]	[0.015]	[0.016]
InGOVSD	0.171	0.166	0.158	0.158	0.155
	[0.007]	[0.005]	[0.004]	[0.013]	[0.026]
InINF	0.152	0.144	0.132	0.112	0.111
	[0.042]	[0.007]	[0.007]	[0.007]	[0.035]
InAGR	0.162	0.122	0.133	0.144	0.151
	[0.005]	[0.041]	[0.008]	[0.007]	[0.027]
InC02	0.111	0.124	0.129	0.131	0.078
	[0.023]	[0.042]	[0.016]	[0.035]	[0.043]
ECL	0.155	0.142	0.151	0.102	0.098
	[0.007]	[0.034]	[0.015]	[0.006]	[0.045]
GOVE	0.169	0.152	0.158	0.158	0.156
	[0.014]	[0.034]	[0.021]	[0.031]	[0.044]
InURB	0.168	0.157	0.172	0.156	0.117
	[0.008]	[0.007]	[0.021]	[0.126]	[0.034]
LEI	0.177	0.163	0.164	0.161	0.111
	[0.021]	[0.043]	[0.013]	[0.114]	[0.036]
EI	0.198	0.187	0.211	0.201	0.188
	[0.035]	[0.036]	[0.019]	[0.119]	[0.026]
COR	0.188	0.177	0.199	0.177	0.167
	[0.015]	[0.016]	[0.016]	[0.114]	[0.015]
Intercept	11.066 ***	32.044			
	[3.544]	[7.633]			
AR(2)test			−2.544	−1.432	−1.435
			[0.105]	[0.113]	[0.109]
Hansen test			33.014	32.189	66.712
			[1.000]	[1.000]	[1.000]

Note: standard errors are reported in []; *** represent 1%. Source: Author's computation 2023.

In column [3] of Table 2, we present the results of the impact of economic growth on RE for the selected economies based on the two-step system GMM. We obtained an estimate of 0.1015 with a 1% level of significance. This suggests that economic growth promotes RE adoption in the selected economies. We validated our results by testing for over-identification restrictions and second-order serial correlation based on $AR(2)$ test and the Hansen test. The ρ-value result of the $AR(2)$ at 0.104 rules out the possibility of second or higher-order serial correlation in the residuals. The results of the Hansen test for over-identification further validated the instruments employed.

A look at the results of other explanatory variates suggests that our results are in line with relevant economic theory and existing empirical findings. For instance, the coefficients of financial development are positive and significant, suggesting that financial development aids the consumption of renewable energy. This supports the finding of [26,69]. The results from each agriculture and trade openness are positive and significant, suggesting that each of them positively supports RE adoption [71]. The results from trade suggest that trade policies such as market liberalization that supports international trade advance the adoption of RE in Africa and, by extension, advance economic growth in the region (see ref. [112]). The result on agriculture suggests that agriculture significantly aids RE adoption in the studied economies and is in line with the findings of [79,81]. As expected, the results on the relationship between RE adoption and inflation are negative and significant. This suggests that with rising inflation, peoples' adoption of RE will be slow as the purchasing power ability of the people is eroded. Our result is in line with the findings of [113].

Our results are mixed for the other explanatory constructs (environmental and socio-political). For instance, while the results from CO_2 emission and ecological footprints are negative and significant, the result from urbanization is positive and significant. This suggests that as these economies get urbanized, the adoption of RE is embraced. This also connotes that, on average, men in these economies are environmentally conscious and friendly. Our results support the findings of [86] for the BRICS economies. The result of CO_2 emission suggests that CO_2 has an inverse relationship with RE in the studied economies (see also ref. [31]). On the socio-political factors, our results also show that governance structure has a positive and significant relationship with RE adoption, suggesting that with a good governance structure, more people will embrace the adoption of RE. The results agree with the findings of [89,92–94] but contradict [71] submission for sub-Saharan African economies.

4.2. Single-Country Estimates Results

Beyond panel estimation, we provide a single-country estimation in our model to account for the heterogeneous behavior of some variables in some of the selected African economies. Hence, our study followed [111–113] to employ a full PMG test for short-run nexus. Before we employed a full PMG model, we conducted unit root tests using In-Pesaran-Shin (IPS), Levin-Lin-Chu (LLC), and cross-sectional augmented Dickey-Fuller test. Our results suggest that none of the variables in the model is found to be $I(2)$). Results are available upon demand. We employed both the Pedroni test and the Westerlund test to conduct a cointegration estimate. The results show that the long-run estimates across all countries are stronger. Results are available upon demand. The result of the full PMG estimate showing country-specific estimate is presented in Table 3. From the results, it can be deduced that the impact of RGDP on RE is positive and significant for Nigeria, Ghana, Kenya, Ethiopia, Morocco, and South Africa, though a negative and significant relationship is noted for Algeria and DR Congo. The results of other macroeconomic variables are similar. For instance, a positive relationship exists between financial development and RE in Nigeria, South Africa, Ghana, and Kenya. The result also shows that foreign direct investment positively impacts renewable energy in Nigeria, Ghana, and South Africa. Trade openness supports RE adoption in Ghana, SA, Kenya, and Nigeria. The inflation rate negatively impacts RE for all the economies studied. On environmental factors, both CO_2 and ecological footprint has a negative and significant impact on RE for Angola, Tanzania, Ivory Coast, Nigeria, Ethiopia, Kenya, and DR Congo. Socio-political factors exhibit some level of positive impact on RE adoption. For instance, urbanization impacts RE adoption positively in South Africa, Nigeria, Ghana, Kenya, Ethiopia, and Angola. Life expectancy and education index impact RE positively and significantly for economies such as Nigeria, South Africa, Tanzania, Kenya, Angola, Ethiopia, and Egypt. The result for corruption index offers mixed results. For instance, it was reported that a negative relationship exists between corruption and RE adoption in Nigeria, Kenya, Ivory Coast, DR Congo, Egypt, and South Africa. Overall examination of our results suggests that most of the studied economies exhibit interacting trends in the adoption of RE.

Table 3. Country-specific full short-run PMG estimates.

Countries	Variables	Coefficients	Countries	Variables	Coefficients
	ECT	0.147 *** (0.027)	Egypt	ECT	0.162 *** (0.023)
	InRGDP	0.063 *** (0.047)		InRGDP	0.043 *** (0.044)
	InFDI	0.042 ** (0.052)		InFDI	0.032 *** (0.053)
	InFD	0.201 * (0.054)		InFD	0.211 * (0.034)
	InTRD	0.0032 *** (0.017)		InTRD	0.0043 *** (0.014)
	InGOVSD	0.0116 *** (0.036)		InGOVSD	0.0115 *** (0.033)
	InINF	−0.017 *** (0.027)		InINF	−0.014 *** (0.024)
Nigeria	InAGR	0.033 *** (0.047)		InAGR	0.023 *** (0.023)
	InC02	−0.012 ** (0.027)		InC02	−0.011 ** (0.024)
	ECL	−0.031 * (0.046)		ECL	−0.021 * (0.043)
	GOVE	0.0158 *** (0.019)		GOVE	0.0128 *** (0.014)
	InURB	−0.019 ** (0.21)		InURB	0.0101 ** (0.011)
	LEI	0.014 *** (0.011)		LEI.	0.013 *** (0.012)
	EI	013 *** (0.003)		EI	0.014 *** (0.006)
	COR	−0.012 ** (0.012)		COR	−0.042 ** (0.013)
	ECT	0.011 * (0.024)	Algeria	ECT	0.014 * (0.021)
	InRGDP	0.032 *** (0.017)		InRGDP	−0.034 *** (0.013)
	InFDI	0.118 *** (0.036)		InFDI	0.114 *** (0.033)
	InFD	0.107 *** (0.017)		InFD	0.104 *** (0.013)
	InTRD	0.013 *** (0.017)		InTRD	0.014 *** (0.015)
	InGOVSD	0.012 ** (0.017)		InGOVSD	−0.013 ** (0.018)
	InINF	−0.031 * (0.042)		InINF	−0.033 * (0.045)
South Africa	InAGR	0.018 *** (0.013)		InAGR	0.015 *** (0.014)
	InC02	−0.109 *** (0.21)		InC02	0.106 *** (0.021)
	ECL	0.0113 *** (0.002)		ECL	0.0115 *** (0.006)
	GOVE	0.013 *** (0.017)		GOVE	0.015 *** (0.014)
	InURB	0.112 ** (0.012)		InURB	0.115 ** (0.014)
	LEI	0.016 * (0.051)		LEI	0.017 * (0.031)
	EI	0.027 *** (0.014)		EI	0.023 *** (0.016)
	COR	−0.111 *** (0.006)		COR	−0.117 *** (0.016)
	ECT	0.117 *** (0.012)	Morocco	ECT	0.114 *** (0.016)
	InRGDP	0.05 *** (0.041)		InRGDP	0.04 *** (0.021)
	InFDI	0.012 ** (0.021)		InFDI	0.011 ** (0.011)
	InFD	0.011 *(0.041)		InFD	0.021 * (0.011)
	InTRD	0.011 *** (0.019)		InTRD	0.013 *** (0.014)
	InGOVSD	0.119 *** (0.21)		InGOVSD	0.114 *** (0.021)
	InINF	−0.015 *** (0.025)		InINF	−0.014 *** (0.022)
Kenya	InAGR	0.13 *** (0.004)		InAGR	0.14 *** (0.004)
	InC02	−0.12 ** (0.012)		InC02	−0.14 ** (0.016)
	ECL	0.012 * (0.014)		ECL	0.015 *** (0.016)
	GOVE	0.012 *** (0.013)		GOVE	0.012 *** (0.016)
	InURB	0.111 *** (0.012)		InURB	0.113 *** (0.015)
	LEI.	0.101 *** (0.02		LEI	0.102 *** (0.031)
	EI.	0.013 *** (041)		EI	0.014 *** (0.051)
	COR	−0.014 ** (0.021)		COR	0.015 *** (0.041)

Table 3. *Cont.*

Countries	Variables	Coefficients	Countries	Variables	Coefficients
Ghana	ECT	0.033 * (0.046)	Angola	ECT	0.07 *** (0.021)
	InRGDP	0.113 *** (0.019)		InRGDP	0.015 ** (0.041)
	InFDI.	001 *** (0.001)		InFDI	0.015 * (0.031)
	InFD	0.012(0.002)		InFD	0.014 *** (0.014)
	InTRD	0.102 *** (0.011)		InTRD	0.114 *** (0.021)
	InGOVSD	0.013 *** (0.011)		InGOVSD	0.013 *** (0.024)
	InINF	0.112 ** (0.072)		InINF	0.015 *** (0.006)
	InAGR	0.011 * (0.001)		InAGR	0.012 ** (0.016)
	InC02	0.023 *** (0.017)		InC02	0.042 ** (0.014)
	ECL	0.016 *** (0.031)		ECL	0.016 *** (0.017)
	GOVE.	0.017 *** (0.021)		GOVE	0.114 *** (0.015)
	InURB	0.053 *** (0.04)		InURB	0.104 *** (0.051)
	LEI	0.012 ** (0.022)		LEI	0.014 *** (0.051)
	EI	0.012 * (0.041)		EI	0.013 *** (0.023)
	COR	0.0118 *** (0.019)		COR	0.005 *** (0.031)
Ethiopia	ECT	0.019 *** (0.021)	Tanzania	ECT	0.015 *** (0.021)
	InRGDP	0.02 * (0.014)		InRGDP	0.014 ** (0.021)
	InFDI	0.011 *** (0.017)		InFDI	0.013 *** (0.014)
	InFD	0.113 *** (0.026)		InFD	0.116 *** (0.21)
	InTRD	0.101 *** (0.011)		InTRD	0.017 *** (0.021)
	InGOVSD	0.013 *** (0.012)		InGOVSD	0.16 *** (0.004)
	InINF	0.014 ** (0.014)		InINF	0.111 ** (0.012)
	InAGR	0.032 * (0.043)		InAGR	0.014 ** (0.014)
	InC02	0.015 *** (0.012)		InC02	0.017 *** (0.014)
	ECL	0.105 *** (0.021)		ECL	0.114 *** (0.013)
	GOVE	0.0115 *** (0.006)		GOVE	0.0011 *** (0.021)
	InURB	0.016 *** (0.012)		InURB.	0.014 *** (0.044)
	LEI	022 ** (0.015)		LEI	0.013 *** (0.021)
	EI	0.017 * (0.052)		EI	0.06 *** (0.051)
	COR	0.024 *** (0.018)		COR	0.015 *** (0.051)
Ivory Coast	ECT	0.113 *** (0.006)	DR Congo	ECT	0.012 * (0.042)
	InRGDP	0.031 * (0.014)		InRGDP	−0.013 *** (0.014)
	InFDI	0.011 *** (0.013)		InFDI	0.114 *** (0.021)
	InFD	0.113 *** (0.032)		InFD	0.013 *** (0.024)
	InTRD	0.107 *** (0.014)		InTRD	0.13 *** (0.004)
	InGOVSD	0.013 *** (0.014)		InGOVSD	0.012 *** (0.012)
	InINF	−0.012 ** (0.017)		InINF	−0.012 ** (0.014)
	InAGR	0.031 * (0.022)		InAGR	0.015 *** (0.015)
	InC02	−0.015 *** (0.014)		InC02	−0.114 *** (0.013)
	ECL	0.105 *** (0.021)		ECL	0.103 *** (0.041)
	GOVE	0.0113 *** (0.002)		GOVE	0.015 *** (0.061)
	InURB	0.013 *** (0.011)		InURB	0.013 ** (0.051)
	LEI	0.112 *** (0.012)		LEI	0.112 *** (0.005)
	EI	0.014 *** (0.031)		EI	0.111 *** (0.014)
	COR	−0.022 *** (0.013)		COR	−0.033 *** (0.014)

Source: Author's computation 2023. Note: *, **, *** represent 10%, 5%, 1% significant level respectively.

5. Conclusions

Decarbonization of the energy sector is at the front burner of the 21st-century energy adoption policy among economies across the world. This is essential to achieving the global quest for sustainable growth via renewable energy that helps in mitigating climate change [10]. A good understanding of the drivers of RE adoption is key to achieving success in RE growth which is essential to attaining sustainable growth. As noted earlier, four macroeconomic-energy possibilities exist in the literature on the link between economic growth and energy. They are the energy-led growth-following hypothesis, growth-led energy-following hypothesis, feedback/bi-directional hypothesis, and neutrality/indifference hypothesis, with each of these possibilities offering unique implications for policy modeling. Beyond macroeconomic variables, environmental factors (such as CO_2 emission and ecological footprint) and socio-political factors (education, life expectancy, and urbanization) often determine the adoption of RE. This paper contributes to the literature by employing appropriate estimation techniques—system GMM and full PMG—to examine the factors that influence the deployment of RE in the African sub-region based on data sourced from 1980 to 2019. Our choice of the system GMM was driven by the possibility that RE adoption and other control variables employed in our model could be jointly determined. The system GMM employed can deal with endogeneity-related issues. It can address the susceptibility of data to measurement error among other things. Validating the orthogonality assumptions in the system GMM, the study employed the Hansen test of over-identification, the Arellano and Bond (2000) test of second-order serial correlation, and the small sample correction of the standard errors.

The results of our estimation techniques and the results from a series of robust tests reveal that the relationship between RE and economic growth in the studied economies is positive and significant, suggesting that RE promotes economic growth on the one hand and economic growth promotes RE adoption on the studied economies, supporting the validity of feedback hypothesis in the studied economies. Hence, policies that support RE adoption should be advanced. A look at other explanatory variables suggests that a positive relationship exists between financial development, foreign direct investment, trade, governance, urbanization, and life expectancy that stimulates RE adoption.

This suggests that for these economies to achieve sustainable growth powered by RE, policymakers need to implement policies that will promote financial development, enhance trade, promote urbanization, and promote education and governance structure. The results of the nexus between inflation and each economic growth and RE adoption are negative, suggesting that policymakers should lower the inflation rate to promote economic growth influenced by RE adoption.

The second strand of our analysis focused on country-specific estimates. From the results, it can be deduced that the results obtained in country-specific estimation are not too far from the ones obtained at the aggregate level. For instance, the connection between RE and economic growth is positive and significant for the economies of SA, Nigeria, and Kenya, suggesting the possibility of a feedback hypothesis.

Though this study has advanced literature by examining the drivers of RE adoption from the point of economic, environmental, and socio-political views, there is a need for further empirical analysis on the subject to further enhance the knowledge of this nexus. Hence, we suggest that further study could examine the impact of RE on total energy adoption in Africa. Different estimation techniques can also be employed.

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Data Availability Statement: We obtained data on macroeconomic variables, including real gross domestic product (RGDP), foreign direct investment (FDI), financial development (FD), trade (TRD), and government spending (GOVT) from the World Development Indicators (various issues). The data on the inflation rate (INF) was sourced from the United Nations Statistics (UN Data). We sourced data on agricultural output (AGRIC) from the Economic Research Service of the US Department of Agriculture (USDA). Data on environmental factors proxy by CO2 emission (thousand kt) and ecological footprint were sourced from the BP Statistical Review of the World Energy (various issues). To account for the impact of socio-political factors, we calibrated the impact of governance effectiveness (GOVE) and urbanization (URB) into our model. Data on these variables were sourced from the World Development Indicators (various issues). We also account for the impact of the life expectancy index, education index, and corruption perception index as part of our socio-political factors in shaping the adoption of RE. Data on the education index (EI) and life expectancy index (LEI) were sourced from the United Nations Development Program (UNDP) development reports (various issues). Meanwhile, data on the corruption perception index (COR) was sourced from the Transparency International database. To address issues relating to heteroscedasticity, we standardized our variables by obtaining their natural log forms. Data on renewable energy were sourced from the International Energy Agency database (various issues).

Conflicts of Interest: The author declares no conflict of interest.

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Article

Medium- and High-Tech Export and Renewable Energy Consumption: Non-Linear Evidence from the ASEAN Countries

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Abstract: Sustaining economic growth while reducing dependence on fossil fuels remains a challenge for our world to fight against climate change and therefore finding a way to promote economic growth and increase renewable energy use is needed. This paper uses a 22-year panel dataset (1994–2015) of 9 countries in the Association of Southeast Asian Nations provided by the World Bank World Development Indicators to examine the impact of medium- and high-tech export on renewable energy use. We employ a fixed-effects regression model with the Driscoll–Kraay nonparametric covariance matrix estimator to account for sectoral and temporal dependence. We also control for inflation, employment, population growth, and gross domestic product per capita in our estimations. Our results demonstrate a U-shaped association between medium- and high-tech export and renewable energy consumption of these economies. The results propose that enhancing medium- and high-tech export could be a feasible solution for promoting renewable energy consumption.

Keywords: renewable energy; medium- and high-tech export; economic growth; employment; inflation; ASEAN

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1. Introduction

Sustaining economic growth while reducing dependence on fossil fuels remains a challenge in our era of climate change. In addition to the need for reducing emissions, continuingly increasing fossil fuel prices, fears of unaffordable and rapidly depleting sources of fossil fuels, and the desire to transitioning into a low carbon economy have combined to heighten the importance of renewable energy use [1]. Several countries have set a target of specific renewable energy share in their total energy consumption. For example, Germany aims to supply electricity solely from renewable energy sources by 2045. China also pledges to be carbon neutral by 2060 and sets the share of non-fossil fuels in primary energy consumption to around 25% by 2030 from a previous commitment of 20%. However, increasing renewable energy consumption is not easy for many developing countries, especially for rapidly growing economies as their demand for energy is increasing and their technical and financial capacities for a large-scale supply of renewable energy are limited. In this regard, looking for possible ways to increase renewable energy consumption while maintaining economic growth is required.

Industrialization generally results in a structural transformation from fossil fuel-based and low technology to clean energy-based and medium- and high technology. Medium- and high-tech industries are the value-added manufacturing sectors with higher technological intensity and productivity. They are referred to the level of technology that companies and industries producing goods with innovative qualifications and advanced technologies [2,3]. High technology industries include, for example, aviation and spacecraft industry, pharmaceutical industry, accounting and information processing technologies, radio, television and communication equipment industry, and medical and optical devices industry [4]. Thus, the production and export of medium- and high-tech products are an important source of export-oriented growth and development, and of the transition to a low-carbon economy [5–7].

There have been several studies on socio-economic factors affecting renewable energy consumption [8–15]. However, new drivers such as medium- and high-tech export have been given much less attention, especially in the context of developing countries [16]. In addition, existing research mainly explores the competitiveness benefit of the policies on renewable energy use in conventional industrial sectors, such as in iron, steel, paper, and glass industries [17]. Globalization has facilitated trade among countries, and the export of medium- and high-tech products have been promoted in rapidly growing economies. However, so far, the causal effects of trade in general, on renewable energy use in both short- and long- terms are weak and scattered [16,18,19], and the effect of medium- and high-tech export on renewable energy use has not been investigated, especially in the context of rapidly growing economies. This is the main motivation for our study.

Theoretically, high- and medium-tech export affect renewable energy use through three channels. First, higher export of high- and medium-tech goods stimulate domestic production of these exported goods and hence economic growth. Increases in domestic production of these goods and economic growth change the energy demand as energy is a key input for production. This is referred to as the scale effect. Second, trade openness allows countries to exchange energy-saving and cleaner energy technologies, which are exported by developed economies and imported by developing economies [20–23]. Such exchange facilitates technological advancement. This is referred to as the technique effect. Third, economic growth leads to economic structural transformation which means that at the beginning of the transformation when the economy is largely agricultural-based, energy intensity is low. However, at a later stage when industrialization starts, energy intensity increases. At the same time, economic growth makes people better-off and increases their awareness of the environment, thus demand more medium and high-tech goods from environmentally friendly producers. This is referred to as the composite effect. The net effect depends on the stage of economic growth and the changes in consumption patterns of consumers. While developed economies have advantages in improving technologies for promoting renewable energy, developing countries are less able to do so and most of them may rely on technology transfers from developed countries, but for various reasons, technology transfers might be constrained. Therefore, at an earlier stage medium- and high-export from developing countries may still demand more fossil-based resources. Later on, renewable energy use will increase.

We focus our analysis on the nine countries of the Association of Southeast Asian Nations (ASEAN), including Cambodia, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Vietnam (hereafter referred to as ASEAN-9 countries). The ASEAN has 10 member countries but we purposely exclude Brunei as its energy consumption solely depends on fossil fuels. Even though these countries differ in several aspects, especially in terms of income per capita (Figure 1), they are commonly known as rapidly growing economies and thus have an increased energy demand. It is projected that the overall primary energy supply will increase from 621 Mtoe in 2015 to 1.544 Mtoe in 2050, an annual increase of 2.6%; and the gross final energy consumption will increase with an annual rate of 2.4%, from 436 Mtoe in 2015 to 1006 Mtoe in 2050. However, ASEAN remains highly reliant on fossil fuels. Nearly 80% of the global primary energy supply by 2050 are projected to adhere to fossil fuels. The heavy reliance on fossil fuels along with the decreasing domestic fossil fuel stocks would force the ASEAN's member states to import more fossil fuels. ASEAN is currently the 3rd largest economy in the Indo-Pacific and the 5th largest economy in the world. It has a combined gross domestic product (GDP) of $US 2.8 trillion, and is also the 3rd fastest-growing major Indo-Pacific economy in the past decade, after China and India (Figure 2). As a critical hub for global trade, over $3.4 trillion in global trade transits through the ASEAN region each year [24]. Their export of medium- and high-tech has also been growing. However, the share of renewable energy in the total energy consumption of these countries is still modest. In this regard, examining the effect of medium- and high-tech export on renewable energy in ASEAN is of particular interest and relevant for policymakers and the public. We use a 22-year panel dataset (1994–2015) of these ASEAN-9 countries provided by the World Bank World Development Indicators to empirically examine the impact of medium- and high-tech export on the share of renewable energy use in total energy consumption of these countries. These countries are diverse in many aspects. For example, Singapore is an advanced economy, Indonesia and Thailand are upper-middle-income countries, Vietnam is a lower-middle-income country, and Cambodia and Laos belong to the group of the least developed countries. Following the arguments in the previous paragraph, we hypothesize that the relationship between medium- and high-tech export and renewable energy consumption in these ASEAN-9 countries is U-shaped.

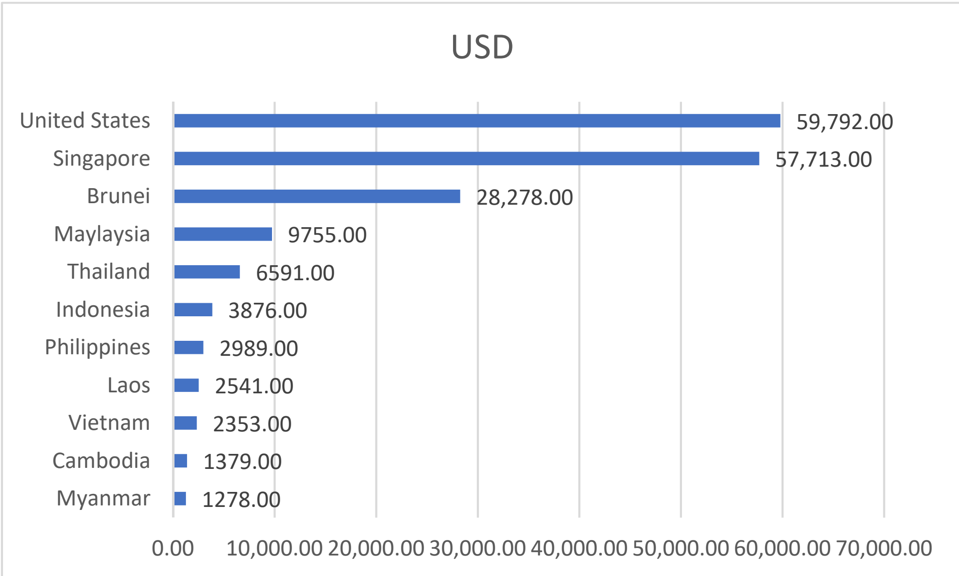

Figure 1. Per capita GDP of the ASEAN economies as compared to the US in 2017. Source: East-West Center, 2019 [24].

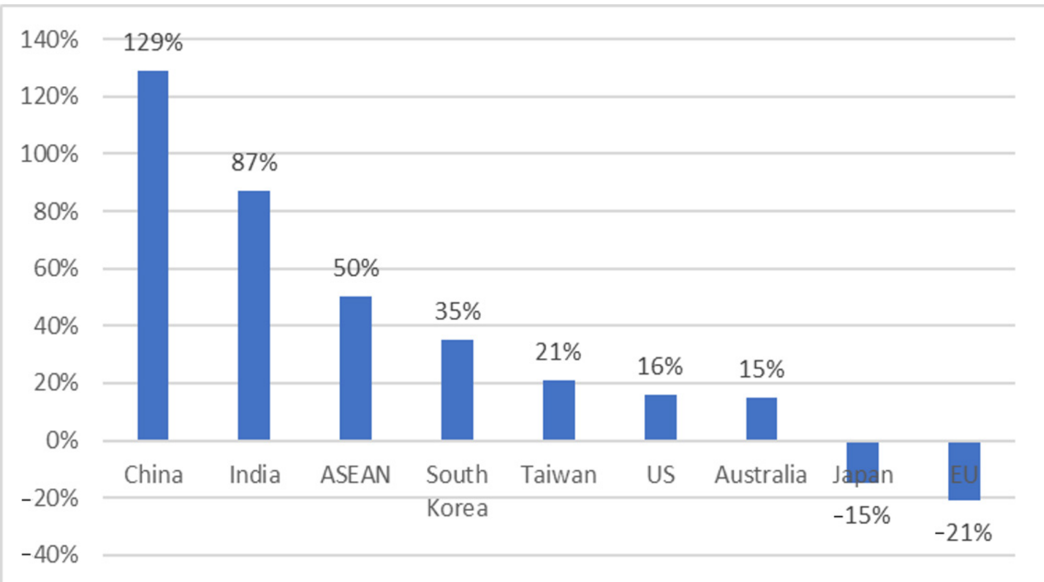

Figure 2. Real GDP growth of ASEAN as compared to some other economies. Source: East-West Center, 2019 [24].

2. Literature Review

As natural resources in general and fossil fuels in particular, have been depleting, renewable energy use and economic growth are highlighted as major concerns for sustainable development of the global economy [25–29], given the fact that the sustainability of the economic system is dependent on the environment and natural resources [30]. Due to an increasing level of globalization, global energy demand has changed over time and has been driven by trade-related factors. Trade openness, export-oriented policies, and internationalization are considered crucial in the long-term development strategy of many developing countries [31,32]. In this context, recent literature has considered new determinants of energy demand and energy intensity such as export or import product portfolio [33,34], trade openness, and technological advancement [35–38]. In general, there is a controversy on the effect of trade on energy intensity. On the one hand, many studies find that trade openness positively affects energy intensity [39–45]. On the other hand, the effect can be adverse [46], or ambiguous [47] depending on competitiveness, factor price, and technology and infrastructure factors ([35,48]). Regarding the spectrum of trade and innovation, Samargandi [35] reveals that trade openness and innovation are significant factors for reducing energy intensity. Beser and Soyyigit [2] indicate that high-tech export has a strong impact on CO_2 emission in developed economies.

The importance of technology in determining energy use and energy efficiency in developing countries is increasing due to a growing level of internationalization and integration [22,49,50]. Technology innovation induced by investment in research and development and by foreign direct investment is supposed to increase energy use efficiency [40]. Domestic innovation is also an important contributor to technical development [49,51]. To mitigate the negative effects of climate change, technological progress is crucial [52], and increased R&D is associated with more technical innovation and renewable energy adoption [53] in both developed and developing countries, where renewable energy sources such as biomass, solar, wind and hydropower are adopted [54,55]. Recent studies on the relationship between technological advancement and carbon emission demonstrate positive effects of technology innovations on carbon emission reduction [56–58]). Liu, Xia, Tao, and Chen [56], for instance, analyze carbon emission in China and find that increasing technological expenditure could in turn increases carbon emission efficiency. Wang, Zhao, Wang, Guo, Kan, and Yuan [57] discover that investments in technology decrease carbon emissions. Zeng, Lu, Liu, Zhou, and Hu [58] find that foreign trade, foreign capital, and technological progress have positive effects on carbon emission reduction.

Several studies examine the drivers of renewable energy use. Most of these indicate the causal interactions between economic growth and renewable energy use [59–62], between renewable energy use and sustainable development [63–65], between energy use and trade openness, and between technological progress and renewable energy use. For example, Apergis and Payne [61] investigate the relationship between economic growth and renewable energy use of 20 OECD countries during 1985–2005 and find a bidirectional link between economic outcome and energy use. Fang and Chang [62] analyze the causality between energy use and economic performance in 16 countries of the Asia Pacific and finds a long-run cointegrating relationship. Kahia et al. [66] examine the relationship between energy use and economic growth, using a sample of 7 MENA Net Oil Importing Countries (NOICs) during 1980–2012; and their empirical results confirm the bidirectional causality between renewable energy use (and non-renewable energy use) and economic growth. Le and Sarkodie [67] investigate the nexus between renewable and conventional energy and economic growth, using panel data of 45 Emerging Market and Developing Economies (EMDEs) from 1990 to 2014. They find that renewable energy and GDP growth impact each other. Marques and Fuinhas [68], using a sample of 24 European countries during 1990–2006, find that the current level of renewable energy use is positively dependent on the previous level of renewable energy use. However, income and prices of fossil-based fuels are not significant for the development of renewable energy during the studied period. Ahmed et al. [69] investigate the interactions between renewable and non-renewable energies, CO_2 intensity, and economic growth in Myanmar during 1990–2016; and their results reveal that renewable energy use significantly promotes economic growth.

Few studies have also examined the relationship between trade openness, technological innovation, and (renewable) energy use (Alam and Murad [16], Sohag, Begum, Abdullah, and Jaafar [22], Sbia et al. [70,71], Khan et al. [72], Cole [47], Shahbaz, Nasreen, Ling, and Sbia [21]). Alam and Murad [16] reveal that economic growth, trade openness, and technological progress significantly influence renewable energy use in 25 OECD countries. Sohag, Begum, Abdullah, and Jaafar [22] employ a dataset during 1985–2012 in Malaysia and find that while economic growth and trade openness are the main determinants of energy use, technological innovation reduces energy use in manufacturing sectors. Sbia, Shahbaz, and Hamdi [70] examine the impacts of foreign direct investment, trade openness, clean energy price, carbon emissions, and economic growth on the demand for energy in the United Arab Emirates. Their findings indicate that trade openness and foreign direct investment reduce energy use because energy-efficient technologies have been employed. By comparing upper-middle-income countries in Asia, Europe, Africa, and America, Khan, Yaseen, and Ali [72] indicate that trade can induce technology transfer for renewable energy. Shahbaz, Nasreen, Ling, and Sbia [21] use the data from 91 high, middle, and low-income economies and conclude that domestic energy use is affected by trade openness through several channels such as technological transfers, economies of scale, and input factors. In high-income economies, an inverted U-shaped relationship between trade openness and energy consumption is found. According to Shahbaz, Nasreen, Ling, and Sbia [21], the U-shaped relationship between trade openness and energy consumption exists when low and middle-income countries import or use energy-efficient technologies from developed countries to lower energy consumption, on the one hand; and on the other hand, when developed countries allow to release those technologies and share profits for low and middle-income countries that have limited access to technology and capital.

A most recent study that is close to our work in terms of geographical coverage (for ASEAN with a 22-year span of time) is Azam, Khan, Zaman, and Ahmad [25], who find that trade openness has a positive relationship with energy consumption in Thailand, Malaysia, and Indonesia. Apart from trade openness, they discover that population growth increases the energy consumption in Malaysia, while it decreases energy consumption in Indonesia. Real GDP is found to have a positive relationship with energy consumption in Thailand, Malaysia, and Indonesia.

The causal effects between international trade (exports or imports) and renewable energy use in both short- and long- terms that have been found so far are weak [16]. The results from Sadorsky [20] for a sample of Middle Eastern countries show that international trade increases domestic use of energy. In addition, Shahbaz, Nasreen, Ling, and Sbia [21] conclude that a U-shaped relationship exists for high-income countries, whereas an inverted U-shaped relationship is found for middle- and low-income countries for the relationship between international trade and energy use.

In sum, none of the previous studies examine the impact of medium-and high-tech export on renewable energy use. Our study is thus aimed to contribute to filling this gap. The contribution of our study to the literature are two-fold. First, our study is the first effort to examine the effects of medium- and high-tech export on renewable energy share in total energy consumption for this group of rapidly expanding economies. To our best knowledge, only Shahbaz, Nasreen, Ling, and Sbia [21] discover non-linear relationships between trade openness and energy consumption for two country groups, high-income countries and middle- and low-income countries. Second, from a methodological perspective, we use panel data and employ a fixed-effects regression model with the Driscoll–Kraay nonparametric covariance matrix estimator to account for unobservable time-invariant factors and sectoral and temporal dependence. These concerns have not been successfully addressed in many previous studies (Azam et al. [25]).

3. Data and Methods

3.1. Data Source

We extract the data needed for our study from the World Bank World Development Indicators (WDI). This database has been established for years in many countries. For the ASEAN countries, the data are available from 1994 to 2015. This allows us to establish a balanced panel dataset for these nine ASEAN countries. As explained above, we exclude Brunei from the sample since it is an outlier in terms of renewable energy use. Our variables of interest are medium- and high-tech export, and renewable energy use of these countries over time as we would like to investigate the association between these two important variables. From the literature review presented in the previous section, it is clear that a direct relationship between them can be established.

We use the share of renewable energy in the total energy consumption of each country in each year (% of total final energy consumption) to represent renewable energy use. It is the explained variable. For explanatory variables, the share of medium- and high-tech export in total manufactured export (% of manufactured export) is our key variable of interest. In addition, we control for inflation, employment, population growth, and GDP per capita. Inflation is measured as the change in the consumer price index (%, year 2010 is the base year, 2010 = 100), employment is measured as the share of employment in the industrial sectors in total employment of an economy in each year (% of total employment) while population growth is also reported annually for each country. The GDP per capita is measured in purchasing power parity (PPP, constant 2017). These variables are coded as follows: *REU* for renewable energy share (%), *MHTE* for medium- and high-tech export share in total manufactured export (%), *INF* for inflation (%), *POPG* for population growth (%), *EMP* for the employment share in industry (%), and *GDPPC* for GDP per capita (PPP, constant 2017). All these variables are annual for these ASEAN-9 countries from 1994 to 2015. A more detailed definition of these variables is in Appendix A. The description of the data for each country is presented in Table 1 whereas Table 2 summarizes the data for the whole block. These tables show the *REU* mean value is 42.673 (%), the mean value of *MHTE* is 37.168 (%), while the mean value of *INF* is 77.034 (%). On average, *POPG* is 1.575%, *EMP* is 17.915 (%), and *GDPPC* is 13,417 (USD PPP 2007). The correlation coefficients between these variables are in Appendix B which show that *NHTE*, *INF*, *POPG*, *EMP*, and *GDPPC* all have a negative association with *REU* at a 1% level of significance.

Table 1. Descriptive statistics of variables of each ASEAN country (1994–2015).

Country	*REU* (%)		*MHTE* (%)		*INF* (%)		*POPG* (%)		*EMP* (%)		*GDPPC* (USD PPP, 2007)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Cambodia	75.59	6.58	3.34	2.93	76.00	25.42	2.01	0.63	12.99	5.50	2118	789
Indonesia	42.65	4.63	29.22	3.70	69.59	36.22	1.38	0.08	19.03	1.29	7150	1501
Laos	75.94	9.94	5.45	4.34	68.51	40.83	1.72	0.27	6.43	2.43	3858	1329
Malaysia	5.79	1.63	67.45	6.13	88.99	13.80	2.00	0.42	30.19	2.17	18,262	3316
Myanmar	80.64	6.29	1.66	2.78	55.45	43.77	0.94	0.23	14.36	2.28	2080	1175
Philippines	32.64	3.78	73.81	10.44	79.34	23.13	1.94	0.27	15.51	0.39	5230	966
Singapore	0.51	0.08	68.87	16.55	92.89	11.308	2.33	1.44	25.03	4.45	65,782	14,060
Thailand	21.85	1.27	58.68	3.99	87.08	15.89	0.74	0.28	20.50	1.65	12,286	2386
Vietnam	48.45	11.12	26.04	10.84	75.46	37.01	1.13	0.26	17.20	4.26	3986	1337

Source: Authors' estimation based on WDI database; SD: Standard deviations.

Table 2. Descriptive statistics of variables of nine ASEAN countries (1994–2015).

Variable	Mean	SD		
		overall	between	within
REU (%)	42.67	29.26	30.29	6.07
MHTE (%)	37.17	29.70	30.26	8.02
INF (%)	77.03	31.26	11.72	29.23
POPG (%)	1.58	0.77	0.55	0.57
EMP (%)	17.92	7.24	6.93	3.07
GDPPC (USD PPP, 2007)	13,419	1983	20,340	4877

Source: Authors' estimation based on WDI database; SD: Standard deviations; No. observations: 198; No. of countries: 9; No. of years: 22.

3.2. Methods

We employ an econometric analysis to examine the effect of the explanatory variable (medium- and high-tech export) on the explained variable (renewable energy share). Following previous studies, we control for GDP per capita, inflation, employment, and population growth as these factors have been found to influence energy use. They are the factors affecting energy demand. GPD per capita, inflation, and employment are key drivers of changes in purchasing power parity; and for population, Samargandi [35] argues that population growth positively influences energy usage and energy intensity, which might be harmful to the environment. The employment share of the industry might have either a positive or a negative on renewable energy use [73–75]. For the effects of these factors on energy use, see [7,16,20–22,35] for GDP, [73,74] for inflation, [75] for employment, and [35,76] for population growth. A factor affecting renewable energy use is its price. The declining price of renewable energy driven by technological progress could be important in increasing the renewable energy share in total energy consumption. Unfortunately, we cannot collect sufficient data. Oil price could be another significant factor. However, as some studies find the least influence of oil price on renewable energy production [7,8,11,20], or insignificant [77], especially in the case of oil-exporting countries like these ASEAN-9 countries, and/or in the case that these countries have subsidized oil prices to avoid any adverse effect of oil price fluctuations on the economy [11]. In addition, incorporating oil prices in our analysis could lead to an endogenous issue that must be addressed. Therefore, we excluded prices factors in our analysis.

Econometrically, the causal relationship could be examined using either a pooled ordinary least square (OLS) technique or the panel data method, including either a fixed-effects model (FEM) or a random-effects model (REM) [78]. To choose either the OLS technique or the panel data method, we conducted an F-test for the joint significance of differing group means. Results of the F-test presented in Appendix C ($F(8, 184) = 76.97$ with p-value 0.0000) indicate the null hypothesis that the pooled OLS model is appropriate is rejected. Thus, panel data analysis was chosen. We advanced further to choose either FEM or REM by performing a Hausman test. Results of this test in Appendix C indicate the FEM is a more suitable specification. From a theoretical point of view, FEM has the advantage of controlling for time-invariant unobservable factors. An alternative test to choose either FEM or REM was the overidentifying restriction test [79,80] which also indicates that the FEM model is a more suitable specification (results of this test in the last two rows in Appendix C). In addition, FEM is also recommended to estimate the parameters for a small cross-sectional sample [81] which is our case as we have only 9 countries. Our specification is also in line with previous studies on factors affecting renewable energy use such as Bamati and Raoofi [7] for 25 developed and developing countries, Alam and Murad [16] for 25 OECD countries, Azam, Khan, Zaman, and Ahmad [25] for three ASEAN countries (namely Indonesia, Malaysia, and Thailand); Kahia, Aïssa, and Lanouar [66] for 7 MENA Net Oil Importing Countries; Marques and Fuinhas [68] for 24 European countries; Sadorsky [20] for eight Middle Eastern countries; Bashir, Sheng, Doğan, Sarwar, and Shahzad [31] for 29 OECD countries; Beser and Soyyigit [2] for G20 countries (except Russia), Chen, Du, Huang, and Huang [5] for 34 industrial sectors in China, and Waheed et al. [82] for 6 Gulf Cooperation and Council countries.

Therefore, our econometric regression model is specified as follows (Equation (1)):

$$REU_{it} = \alpha_0 + \beta_1 MHTE_{it} + \beta_2 INF_{it} + \beta_3 POPG_{it} + \beta_4 EMP_{it} + \beta_5 PGDPC_{it} + v_i + e_{it} \quad (1)$$

where *REU* is the share of renewable energy in total energy consumption; *MHTE* is the share of medium- and high-tech export in total export; *INF* is the inflation rate; *POPG* is the population growth rate; *EMP* is the employment share of industry (%), and *GDPPC* is GDP per capita (PPP, constant 2017) as defined in Section 3.1 (see Tables 1 and 2). Subscripts i and t denote country and time, respectively; α is the fixed country effect while v_i is the country-specific effect, and e_{it} is the error term.

Several tests were undertaken to ensure the validity of our regression model. First, to control for possible multicollinearity between explanatory variables, the variance inflation factor (VIF) values were checked [83,84] and the results documented in Appendix D do not signal that problem. Second, as our sample is small in terms of both the number of countries (9 countries) and the number of time periods (22 years), we undertook the following tests: (i) Modified Wald test for group-wise heteroskedasticity, (ii) the Breusch–Pagan LM test for cross-sectional dependence [85,86]; (iii) the slope homogeneity test introduced by Swamy [87], and (iv) the stationarity test for each variable.

Cross-sectional heterogeneity should be controlled for when conducting a panel data empirical analysis [88]. Swamy [87] proposes the homoskedasticity assumption test for the slope homogeneity assumption. Results of this test presented in Appendix E show that we can reject the null hypothesis of the slope homogeneity for our sample. In addition, results of the Breusch–Pagan LM test of independence (also in Appendix E) indicate that the null hypothesis of no cross-sectional independence is rejected at the 1% level of significance, indicating strong cross-sectional dependence.

Once there is cross-sectional dependence across countries in the panel, it is needed to perform the cross-sectionally augmented Dickey-Fuller (CADF) procedure from Pesaran [89]. Results presented in Appendix F show that we were not able to reject the null unit root hypothesis for the *GDPPC* series; but when taking the first difference, the null hypothesis of the unit root is rejected for variables POPG and INF. However, this is not sufficient for us to conclude that there is a long-run equilibrium relationship among the concerned variables, namely *REU*, *MHTE*, *INF*, *EMP*, *POPG*, and *GDPPC*.

Given the presence of cross-sectional dependence and/or heteroscedasticity, we adopted our FEM with Driscoll–Kraay standard errors. According to Hoechle [90], the Driscoll–Kraay standard errors are heteroskedasticity-, and autocorrelation-, consistent and robust to general forms of cross-sectional and temporal dependence.

4. Findings and Discussion

4.1. Findings

Table 3 presents the results of our estimation, including both a normal fixed effects specification and the fixed effects specification with the Driscoll–Kraay standard errors. The R squared value of 0.718 from these two specifications indicates that shows our model can predict about 72% of the variation in the share of renewable energy in total energy consumption.

Regarding the effect of medium- and high-tech export, Table 3 shows that the medium- and high-tech export has a significant U-shaped relationship with the share of renewable energy use of these ASEAN-9 countries. This U-shaped relationship implies that at the beginning stage of economic development, a higher level of medium- and high-tech export would lead to a lower share of non-renewable energy in total energy consumption. However, once the economy has reached a certain level of medium- and high-tech export, then the higher the level of medium- and high-tech export, the higher the share of renewable energy in the total energy consumption of that economy. In our case, the threshold value for the turning point of the U-shaped relationship is 64.47%. Within these ASEAN-9 countries, Malaysia and Singapore have passed this turning point since 1994, and the Philippines since 1995.

With regards to the controlled variables, inflation, employment in the industry sector, and GDP per capita are significantly and negatively associated with the share of renewable energy in total energy consumption, meanwhile, population growth is significantly and positively associated with the share of renewable energy.

Table 3. Impact of medium- and high-tech export on renewable energy share.

Variable	Normal Fixed Effects Model	Fixed Effects Model with xxx Driscoll-Kraay Standard Errors
MHTE	−0.420 *** (0.105)	−0.420 ** (0.163)
MHTE, squared	0.0036 *** (0.0011)	0.0036 ** (0.0015)
INF	−0.0895 *** (0.0133)	−0.0895 *** (0.0130)
POPG	0.989 * (0.518)	0.989 * (0.476)
EMP	−0.719 *** (0.121)	−0.719 *** (0.199)
GDPPC	-7.29×10^{-5} (7.32×10^{-5})	-7.29×10^{-5} (0.0001)
Constant	69.28 *** (2.460)	69.28 *** (3.043)
No. of observations	198	198
No. of time periods	22	22
No. of countries	9	9
F test that *MHTE* and *MHTE* squared are jointly equal to zero	F(2, 183) = 8.46 Prob > F = 0.0003	F(2, 8) = 3.32 Prob > F = 0.0890
Overall R squared	0.718	0.718

Source: Authors' estimation, standard errors in parentheses, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.2. Discussion

With respect to the influences of medium- and high-tech export on renewable energy use, our results indicate that medium- and high-tech export has a U-shaped association with renewable energy use in the ASEAN-9 countries. A couple of previous studies have not found any short- and long-term effects of trade on renewable energy use [8,91]. Our finding is a contribution to a new strand of literature on the non-linear effects of trade on resource use. This strand includes, for example, Shahbaz, Nasreen, Ling, and Sbia [21] who find the pattern of a U-shaped relationship exists in high-income countries, and an inverted U-shaped relationship in the middle- and low-income countries for the relationship between international trade and energy use.

Most previous studies so far have found only a positive effect of high-tech export. It is generally argued that under high-tech export orientation, there is peer-to-peer lending which enables them to adopt such technology that uses lower energy; in addition, different technologies and resources can be shared. Thus, energy consumption is also shared and reduced and it helps save energy costs, including renewable energy [2,7]. Bamati and Raoofi [7] provide an analysis of the influence of high-tech export on renewable energy production by levels of development and find that high-tech export increases renewable energy production for 10 developed countries, but for 15 developing countries the effect is insignificant. A stronger effect of high-tech export on developed countries rather than developing countries is also confirmed by Beser and Soyyigit [2] with a sample of the G20 countries (except Russia).

Our result can be explained by the fact that, in terms of medium- and high-tech export, most of the ASEAN-9 countries do not seem to have high shares of high-tech export or at least technologies that could affect promoting renewable energy use. This means, at a lower level of development, the effect is negative but later on, it turns out to be positive.

Renewable energy use is upon the spending and expectations toward the behaviors of consumers that are affected by different aspects of inflation [92–94]. While depicting the concern of medium- and high-tech export toward renewable energy use, the controlled factors have a specific influence on renewable energy use in the ASEAN-9 countries. This is widely stated by the variables like GDP per capita and employment. Inflation is also counted as a major factor that influences renewable energy use. Inflation has a dominant impact on economic performance due to the implications of targeting the environment by high inflation [73]. Our results indicate that inflation has a negative relationship with renewable energy use. These results are supported by Kosai, Yuasa, and Yamasue [74]. Although prices of various products are associated with inflation and wide interpretation enhances the role of renewable energy use in the ASEAN-9 countries, a hike in prices of various goods and services induces a significant impact on renewable energy use. Therefore, inflation with the relevance of medium- and high-tech export inserts a negative role toward the renewable energy use of many ASEAN-9 countries [95]. It could be due to the devaluation of the currency that renders renewable energy use with a hike in prices. Inflation could help in uplifting the economies of various countries but could lead to some adverse effects too.

Our regression model shows that population growth has a positive effect on renewable energy use. In fact, the introduction of technology and innovation in renewable energy use has increased the demand of the population for renewable energy. While enumerating the ecological problems with energy-related factors, population growth is the main driver of environmental degradation [96]. Therefore, population growth might result in a negative contribution toward renewable energy use. Our results contribute, to some extent, to this disputable discussion. Recall that Azam, Khan, Zaman, and Ahmad [25] when examining the impact of various factors on energy consumption in three ASEAN countries (Indonesia, Malaysia, and Thailand) in the period 1980–2012, find that population growth increases the energy consumption in Malaysia, while it decreases energy consumption in Indonesia.

The advantage of renewable energy use is indisputable. It is upon the governments of these ASEAN-9 countries to induce needed measures to promote energy use. Potential impacts of employment on renewable energy use in various industries are evident with local renewable resources [97]. Many ASEAN-9 countries have contributed to a significant rise in the employment rate due to its influence on renewable energy use. For the regional development policy of renewable energy use, the employment regimes and challenges insert an important role [98]. The improper sharing of the economy has been eliminated by the positive enclosure of employment elements that widely induce technological innovation in ASEAN-9 countries.

The empirical results also show that GDP per capita has a negative but insignificant effect on renewable energy use. The result is in line with Marques and Fuinhas [68] who investigate drivers promoting renewable energy in 24 European countries and find that the per capita income (in natural logarithm) is not statistically significant in explaining the use of renewables. A negative effect is found by Waheed, Sarwar, and Mighri [82], and Samargandi [35]. Samargandi [35], for example, examines the impacts of trade openness, technological innovation, and energy price on energy intensity in OPEC countries, in which GDPPC is used as a controlling variable.

5. Conclusions

Our study investigates the influences of medium- and high-tech export on the renewable energy use of nine ASEAN countries in the period 1994–2015. We control for inflation, population growth, employment, and GDP per capita. Our findings suggest that medium- and high-tech export reduces the share of renewable energy in total energy consumption during an earlier stage of economic development but then increases the share of renewable energy consumption during the later stage of economic development. This seems to be a characterized feature observed in these ASEAN-9 countries, contributing to the complexity of trade-renewable energy nexus in the literature. Our study also elaborates that under high inflation, individuals and firms cannot afford costly high technology, effective techniques, and skilled human resources, which consume a smaller amount of renewable energy in production. Growth in the population provides human resources and at the same time promotes renewable energy use. High employment opportunities indicate high economic growth, which can help to save energy.

Our study has some limitations despite its theoretical and empirical importance. First, due to the availability of the data provided by the World Bank in the World Development indicator, we are not able to control for other factors such as oil prices and/or price of renewable energy that might have significant effects on renewable energy use. Therefore, our results should be interpreted with care. Second, our study is at the macro level and thus not on the behavior of individual energy users (i.e., firms and businesses). The changes in the behavior of energy users should be examined as well to provide a better understanding of energy transition. Third, our sample is small with only nine ASEAN countries in a short-term period. Expanding the study to cover more countries in a longer time period would provide a more comprehensive picture of the effect of medium- and high-tech export on renewable energy use. Last, we are unable to undertake a measurement uncertainty analysis [99]. These issues should be themes for future studies.

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Appendix A. Definition of Variables Used in the Analysis

Variable	Definition & Measurement
REU	Share (%) of renewable energy consumption in total final energy consumption in a year of a country
INF	Change (%) in consumer price index with year 2010 as the base year (100%). It reflects changes in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals. It is annual for each country.
EMP	Share (%) of employment in industry in total employment of an economy. Employment is defined as persons of working age who are engaged in any activity to produce goods or provide services for pay or profit, whether at work during the reference period or not at work due to temporary absence from a job, or to working-time arrangement. The industry sector consists of mining and quarrying, manufacturing, construction, and public utilities (electricity, gas, and water), in accordance with divisions 2–5 (ISIC 2) or categories C-F (ISIC 3) or categories B-F (ISIC 4).
POPG	Annual growth (%) of the population of a country
GDPPC	GDP per capita measured in purchasing power parity (PPP) 2017. PPP GDP is gross domestic product converted to international dollars using purchasing power parity rates. An international dollar has the same purchasing power as a U.S. dollar has in the United States. GDP at purchaser's prices is the sum of gross value added by all resident producers in the country plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources.
MHTE	Share (%) of medium- and high-tech export in total manufactured export

Source: WDI.

Appendix B. Correlation Matrix of the Variables Used in the Analysis

Variable	*REU*	*MHTE*	*INF*	*POPG*	*EMP*	*GDPPC*
REU	1.0000					
MHTE	−0.9015 ***	1.0000				
INF	−0.4541 ***	0.3562 ***	1.0000			
POPG	−0.1662 ***	0.2578 ***	−0.1246 *	1.0000		
EMP	−0.8293 ***	0.6782 ***	0.4239 ***	0.07722	1.0000	
GDPPC	−0.6737 ***	0.5109 ***	0.3077 ***	0.2964 ***	0.4741 ***	1.0000

***, **, and *: Significant at the 1%, 5% and 10% level, respectively. Source: Authors' estimation.

Appendix C. F test, Hausman Test, and Test of Overidentifying Restrictions

F Test	Coef.
F test that all u_i = 0: F(8, 184)	76.97
p-value	0.0000
Hausman Test	**Coef.**
Chi-square test value	40.83
p-value	0.0000
Test of overidentifying restrictions: fixed vs. random effects	
Sargan–Hansen statistic Chi-sq(5)	51.628
p-value	0.0000
Source: Authors' estimation.	

Appendix D. Variance Inflation Factor (VIF) Value

Variable	VIF	1/VIF
MHTE	2.15	0.464597
EMP	2.08	0.479953
GDPPC	1.53	0.651664
INF	1.33	0.753238
POPG	1.23	0.813535
Mean VIF	1.67	
Source: Authors' estimation.		

Appendix E. Cross-Sectional Dependence, Heteroskedasticity, and Slope Homogeneity Tests

Breusch-Pagan LM Test of Independence	Coef.
Chi-square test value: χ^2 (36)	134.156
p-value	0.0000
Modified Wald test for groupwise heteroskedasticity	
χ^2 (10)	509.54
p-value	0.0000
Swamy slope homogeneity test	
Chi-square test value: χ^2 (48)	41658.21
p-value	0.0000

Note: The null hypothesis of the cross-sectional dependence test is no cross-sectional dependence. The null hypothesis of the slope homogeneity test is slope homogeneity. The Cross-sectional dependence and slope homogeneity tests are conducted by using respectively 'xttest2' [100] and 'xtrchh2' [101] commands in Stata. Source: Authors' estimation.

Appendix F. Panel Unit Root Test

Variable	Level (CIPS)		1st Difference (CADF)	
	Intercept	Intercept and Trend	Intercept	Intercept and Trend
REU	−2.055	−1.883	−0.913	1.004
MHTE	−0.865	−1.4615	1.977	1.2513
INF	−1.683	−2.435	0.671	−1.499 *
POPG	−3.124	−2.536	−2.927 ***	5.047
EMP	−1.507	−1. 670	1.081	1.339
GDPPC	−1.437 ***	−1.784 ***	0.839	1.452

Note: *** and * denote statistical significance at the 1% and 10% levels, respectively. The null hypothesis is nonstationarity. The panel unit root test is conducted by using the 'xtcips' command in Stata [102]. Source: Authors' estimation.

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Article

Assessing the Economic and Environmental Impacts of Alternative Renewable Portfolio Standards: Winners and Losers

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Abstract: State-mandated renewable portfolio standards affect substantial portions of the total U.S. electricity supply. Renewable portfolio standards are environmentally motivated policies, yet they have the potential to greatly impact economy. There is not an agreement in the literature on the impact of renewable portfolio standards policies on regional economies, especially on job creation. By integrating various methodologies including econometrics, geographic information system, and input–output analysis into a unique system dynamics model, this paper estimates the economic and environmental impacts of various renewable portfolio standards scenarios in the state of New Mexico, located in Southwestern U.S. The state is endowed with traditional fossil fuel resources and substantial renewable energy potential. In this work we estimated and compared the economic and environmental tradeoffs at the county level under three renewable portfolio standards: New Mexico's original standard of 20% renewables, the recently adopted 100% renewables standard, and a reduced renewable standard of 10%. The final one would be a return to a more traditional generation profile. We found that while the 20% standard has the highest market-based economic impact on the state as a whole, it is not significantly different from other scenarios. However, when environmental impacts are included, the 100% standard yields the highest value. In addition, while the state level economic impacts across the three scenarios are not significantly different, the county-level impacts are substantial. This is especially important for a state like New Mexico, which has a high reliance on energy for economic development. A higher renewable portfolio standard appears to be an economic tool to stimulate targeted areas' economic growth. These results have policy implications.

Keywords: renewable portfolio standards; employment; economic output; water use; greenhouse gases; emissions; social benefits

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1. Introduction

Electric utilities in the United States (U.S.) are integrating more renewable energy (RE) sources in their energy mix. In May 2020, 24.3% of electricity generation in the U.S. came from renewable sources (Energy Information Administration, Form EIA-860M). This is partly a result of policies and regulations aimed at mitigating greenhouse-gas (GHG) emissions through programs such as the Regional Greenhouse Gas Initiative in the northeastern part of the U.S., and through the renewable portfolio standard (RPS) at the state level. While the primary objective of these regulations is to address global warming, there can be potential impacts on the economy at a microlevel (i.e., state and county levels). For rural western states, this has become increasingly important, as they strive to diversify their economies.

Debates are ongoing in the literature as to whether RPS policies have a positive (i.e., job creation, GHG and air pollution reduction), negative, or no impact on an economy and the environment (e.g., [1–5]). The main reason for the divergent findings is the inclusion or exclusion of market failure due to environmental amenities in the analyses. For example, NYSERDA [1] assessed New York's RPS impact and found a gain of 24,000 job-years from 2002 to 2037. Divounguy et al. [2] investigated Ohio's 12.5% by 2025 RPS and found that it would result in a loss of more than 134,000 jobs. Upton and Snyder [3] evaluated states with an RPS versus those without, and they found that an RPS standard has no significant impact on increasing RE or reducing GHGs. Zhou and Solomon [4] found that more stringent RPSs result in lowering RE capacity additions, while Carley et al. [5] found the opposite. Further, most of the existing literature focused on either an aggregate scope (e.g., nation-wide) or state-specific assessments and has not considered impacts at lower-level jurisdictions (e.g., county level). Lastly, much of the literature overlooked the fundamental dynamics within the energy sector. The objective of this paper is to contribute to this line of research and assess the economic and environmental impact of renewable energy and the tradeoffs on a regional economy.

In particular, we are interested in answering the question of what are the economic and environmental impacts of varying RPSs on regional economies. This is a rather complex question, and answering it is aided by the use of system simulation [6–11]. Thus, in this work we develop, validate, and utilize a system dynamics (SD) based simulation model that integrates results from various methodologies such as input–output analysis, econometrics, and Geographic Information System (GIS). Combining these methodologies in an innovative approach to analyze the SD model is one key contribution of this paper. We execute our analysis in our case study of New Mexico, a southwestern state in the U.S. with an RPS and high potential for both fossil fuel (traditional) and RE sources. We hypothesize that RPS levels have substantial environmental and economic impacts on regional economies. This paper is an attempt to quantify those impacts.

Our findings suggest a net increase of jobs in rural counties that are most suitable for future RE installations. Depending on the scenario, our model estimated increasing 137–156 thousand cumulative, full-time equivalent jobs, 19 to 24 billion USD (2017$) cumulative gross economic output, and 12,987 to 13,219 and 974 to 1122 billion liters of cumulative water withdrawal and consumption respectively from 2017 to 2050. These scenarios also resulted in increasing millions of avian mortalities, as well as millions of tonnes of GHG emissions and thousands of tonnes of air pollutants, each of which leads to billions of dollars in climatic and air-quality costs (social costs). Lastly, we found that higher RPS standards lead to greater benefits to the state when externalities and social benefits/costs are taken into account.

2. Background

The burning of fossil fuel (i.e., coal, natural gas, and oil) is the main source of GHG emissions in the U.S., and this contributes to climate change. Combusting fossil fuels for electricity generation not only emits air pollution but also requires an immense amount of water. There is extensive literature that demonstrates the correlation between air pollution and premature mortality/morbidity [12–18]. Maupin et al. [19] showed that roughly 40% of all of the U.S. freshwater withdrawal was used for thermoelectric power plants in 2010. Policymakers, as a result, are seeking to promote policies that lead to integrating more environmentally friendly generation sources with less externalities.

Electricity generation is moving towards integrating a higher level of RE and a lower level of fossil fuels in the U.S. due to regulatory mandated laws such as the RPS as well as cost competitiveness. Thirty states and the District of Columbia currently have an RPS in place. RPSs mandate that electric utilities source a portion of their generation from RE within a certain timeframe. Although the main goal of an RPS is environmentally oriented—that is, to mitigate GHG emissions and/or save water—these policies have the potential to impact economies. Previous research on the impact of RPSs shows that the policies are capable of yielding positive economic impacts if positive externalities (zero or close to zero water usage, zero emission, etc.) are taken into account [20,21]. Barbose et al. [20] demonstrated that meeting requirements mandated by RPSs led to supporting

200 thousand jobs and a reduction of 59 million tonnes of CO_2 in the U.S. in 2013. Wiser et al. [21] quantified positive externalities of RE and estimated that existing RPS policies lead to improving air quality and reducing climatic damages (258 billion USD), which not only compensates the increase in electric system costs (23 to 194 billion USD) but also exceeds those costs over the period of 2015–2050.

There are a handful of peer-reviewed papers and national laboratory reports that look at the feasibility of providing global energy through RE (e.g., [22–25]). For example, Jacobson and colleagues [22] estimated a portfolio mix that enables the United States to sustain its entire energy needs—including electricity, transportation, heating/cooling, and industry—using renewable energy by 2050. Similarly, Cole et al. [25] assessed different scenarios of achieving various levels of RE in only the power sector by 2050. Further, previous economic impact studies of constructing and operating RE projects suggested that the economic impacts to states are considerable [17,26,27]. Similarly, studies on environmental impact of RE showed significant climate and air quality benefits [28–31]. For instance, Millstein et al. [29] found that solar and wind development resulted in benefits of 30–113 billion USD (2015) and 5–107 billion USD from air quality and climate, respectively, while avoiding 3000–12,700 premature mortalities in 2007–2015. Most of these studies produced state-level or nation-wide job/environmental impact estimates, which in turn meant less understanding of lower-level dynamics such as job/environmental impacts across counties. These studies also did not consider the underlying dynamics within the energy sector.

To address the aforementioned gaps in the literature, we combine various methodologies to develop an SD model. SDs are a derivative of the work developed by Forrester [32], in which he introduced a novel approach to integrate multiloop feedback systems. So long as relationships among variables are known, this approach makes modeling complex systems possible [33]. The SD model of this paper integrates results from input–output analysis, econometrics, and GIS to form a unique framework that provides both the public and policymakers improved information with which to make decisions. The model is developed at a monthly time-step from January 2004 through January 2050. Multiple programs are used to analyze the complex electricity problems common to most utilities. Specifically, Jobs and Economic Development Impact (JEDI) coupled with Impact Analysis for Planning (IMPLAN) are used to calculate job multipliers by energy type and by county; Stata is used to estimate electricity demand; ArcGIS is utilized to estimate the potential of renewable and natural gas electricity generation by county, as well as the optimal location for siting additional power plants; lastly, results from previous models are all embodied in Powersim Studio, which is used to analyze various energy mix scenarios.

The objective of the SD model is to estimate electricity generation and consumption by different fuel sources and various sectors respectively. We provide a roadmap to assess the explicit and implicit impacts of various energy mix scenarios at the state and county level and at different points in time. Explicit impacts may include potential jobs and economic gross output associated with current and potential future electricity generation, and implicit impacts may include positive health effects and social benefits of reducing ambient emissions. We apply this roadmap to our case study of New Mexico.

2.1. Study Area: New Mexico

New Mexico has considerable potential for both fossil fuel and RE resources. It holds about 3%, 4%, and 5% of the United States' total estimated recoverable coal reserves, proved crude oil, and natural gas respectively and it possesses the second-largest uranium reserves in the nation. Most of the state's natural gas and crude oil are located in the San Juan and Permian Basins in the northwestern and southeastern part of the state, respectively, while coal reserves are mainly located in the San Juan and Raton Basins in the northern part of the state. The vast areas of New Mexico with available geophysiological landmass that receives high wind and sunlight levels are optimal for increasing RE usage. New Mexico ranks third in both solar and wind potential in the U.S. [34].

New Mexico's economy is ranked 46th in the nation. The energy industry, especially oil and natural gas extraction, is a main contributor to New Mexico's economy. The state receives approximately 2 billion and 300 million USD per year in direct (e.g., severance, property taxes, royalty, and rental income) and indirect (sales and income taxes) revenues, respectively, from oil and gas production. Depending on the state of the economy, based on recent state finance facts, revenues from oil and gas can contribute about 40% to New Mexico's general fund tax revenue. Thus, fluctuating oil and gas prices affect New Mexico's economy immensely.

On one hand, the energy industry is responsible for emitting GHG and ambient pollution as well as increased water usage in New Mexico. GHG contributes to climate change, while air pollution causes premature mortality and morbidity, and freshwater has historically been insufficient in New Mexico. On the other hand, RE is becoming more and more cost-competitive compared to fossil fuel technologies. Thus, it makes logical and economic sense for policymakers to promote policies such as an RPS in order to integrate more RE into New Mexico's energy mix.

At the time of analysis, New Mexico's RPS required all large electric utilities to generate 20% of their in-state electricity sales from RE resources by 2020. Although it did not pass, a bill (Senate Bill 312) was introduced to increase New Mexico's RPS previous level to 25% by 2020, 35% by 2025, 50% by 2030, 65% by 2035, and 80% by 2040 in the 53rd legislative session in 2017. A modified version of this bill was reintroduced in January 2019 (House Bill 15) and was passed in the 54th legislative session in March 2019 (Senate Bill 489). In addition to the requirements set by Senate Bill 312, Senate Bill 489 sets a 100% RPS by 2045 that is sourced from zero carbon resources. This makes New Mexico the third state in the U.S. after California and Hawaii and before Washington, New York, Maine, and Virginia to mandate a 100% RPS. Thus, New Mexico's current RPS policy requires 20% in-state electricity sales from RE resources by 2020, 40% by 2025, 50% by 2030, 80% by 2040, and 100% by 2045.

Currently, there are three large electric utilities in New Mexico: the Public Service Company of New Mexico, El Paso Electric, and Xcel Energy, with the first serving the largest customer pool in the state. Further, as New Mexico has considerable potential in both wind and solar energy, the Public Regulation Commission set diversity targets (carve-outs) for different types of RE to create a diversified portfolio. Based on this portfolio, the utilities are required to source at least 30%, 20%, and 3% of their in-state electricity sales from wind, utility-scale photovoltaic solar (PV), and residential photovoltaic solar (RPV), respectively, by 2020 (see Table 1). RPS requires the New Mexico's rural electric distribution cooperatives to generate 10% of their in-state electricity sale from renewable sources. We did not consider a rural cooperatives constraint in our analysis.

Table 1. Carve-outs regulated by renewable portfolio standard.

Source	Minimum Amount
Wind	30%
Utility-scale solar (PV)	20%
Residential/distributed solar (RPV)	3%

2.2. Scenario Construction

Our analysis investigated the number of jobs and their locations by energy source, as well as environmental impact based on thirty-four prices, three technological-costs, and three RPS scenarios. Each of these scenarios are described briefly below.

We adopted 34 price scenarios—i.e., electricity price by sector, Henry Hub natural gas price, and electric sector fuel cost (coal and natural gas)—developed by the Energy Information Administration's (EIA) Annual Energy Outlook 2018 (AEO2018), along with three technology cost scenarios developed by the National Renewable Energy Laboratory (NREL) [25]. A list of AEO2018 scenarios are summarized in the supplementary document (Table S1). The cost scenarios includes low, mid, and high (constant) cost and performance estimates for wind, PV, RPV, natural gas (both baseload (combined-cycle; NGb) and peaker (single-cycle; NGp)), and coal from 2016 to 2050. Low-cost wind and solar scenarios utilize low-cost estimates for land-based wind, along with PV and RPV technologies, while high-cost scenarios use constant costs at or near the 2018 cost estimates. The mid-case scenario assumes prospective advances in the RE arena technology. The low- and high-cost scenarios for fossil fuel beyond 2016 relies on two case estimates from AEO2018, i.e., the high oil and gas resource and technology case and the low oil and gas resource and technology case, respectively. The mid-case scenario serves as a reference case for fossil fuel technology costs adopted from AEO (2018). Overall, the SD model is capable of assessing 918 ($34 \times 3 \times 3 \times 3$) different scenarios. For the purpose of brevity, we focus on the three most plausible future scenarios: the new RPS, the previous RPS, and a future where integrating RE in the electric grid is discouraged. Under the first scenario, i.e., 100% RPS, we assume a future with scarce natural resources with costly fossil fuel and cheap RE technologies that make 100% RPS by 2050 possible. The second scenario, i.e., 10% RPS, is the opposite of the first scenario, in that we assume abundant natural resources with cheap fossil fuel and expensive RE technologies, hence a decreased RPS (10% by 2050). Lastly, we implement a status quo scenario, i.e., 20% RPS, that assumes reference case AEO prices with mid-case technology cost of fossil fuel and constant RE technology cost, along with business-as-usual RPS (RPS 20% by 2020 and on). Below we summarize each scenario.

I. 100% RPS: AEO price = low oil and gas resource and technology; RE cost = low; fossil fuel cost = high; RPS = Senate Bill RPS (100%)
II. 10% RPS: AEO price = high oil and gas resource and technology; RE cost = high; fossil fuel cost = low; RPS = decrease RPS (10%)
III. 20% RPS: AEO prices = reference case; RE cost = high; fossil fuel cost = mid; RPS = status quo RPS (20%)

3. Materials and Methods

Our model consists of five submodels: (1) demand; (2) supply; (3) gap between supply and demand (hereafter "gap"); (4) jobs; and (5) environmental impact, with more than 1200 variables. The first submodel consists of two modules that together estimate electricity demand beyond 2016. The second submodel includes six modules that altogether project megawatt-hour (MWh) generation. The gap and the jobs submodels each contain seven modules. Finally, the environmental impact submodel contains only one module. A detailed description of the model is provided in the Supplementary Materials (Section B) and a related work [35]. Here, we briefly describe the overarching dynamics of the model.

Our model is based on a series of stocks and flows. Stocks can change from period to period; the changes are governed by "flows". The flows, based on either natural science-based rules, human choice, or policies, or a combination thereof, are the set of rules that dictate the change in the stocks. Figure 1 provides a schematic of the model. Arrows provide the connections between stocks and flows. In all cases, the arrows represent the direction of interaction. Associated with each stock, flow, and connecting arrow is a set of quantifiable relationships and rules that allow us to model the system and assess the impact and tradeoffs between sectors within a time period as well as over time.

The basic structure of the modeling components is the physical market for electricity, which (in the figure) is at the intersection of supply and demand and is governed by an exogenous price path. As mentioned in the scenario definitions section, we implemented 34 price scenarios developed by EIA's 2018 AEO report. Thus, "exogenous" here does not mean a fixed value over time but rather is a given independent variable that fluctuates by month and over time. Supply depends on capacity and capacity utilization, which is aggregated from individual generation sources of capacity, utilization, and net exports into/out of state, while demand depends on in-state (domestic) consumption. In-state demand is the aggregation of individual sectoral demands, which can be impacted by market conditions (price) and population impacts.

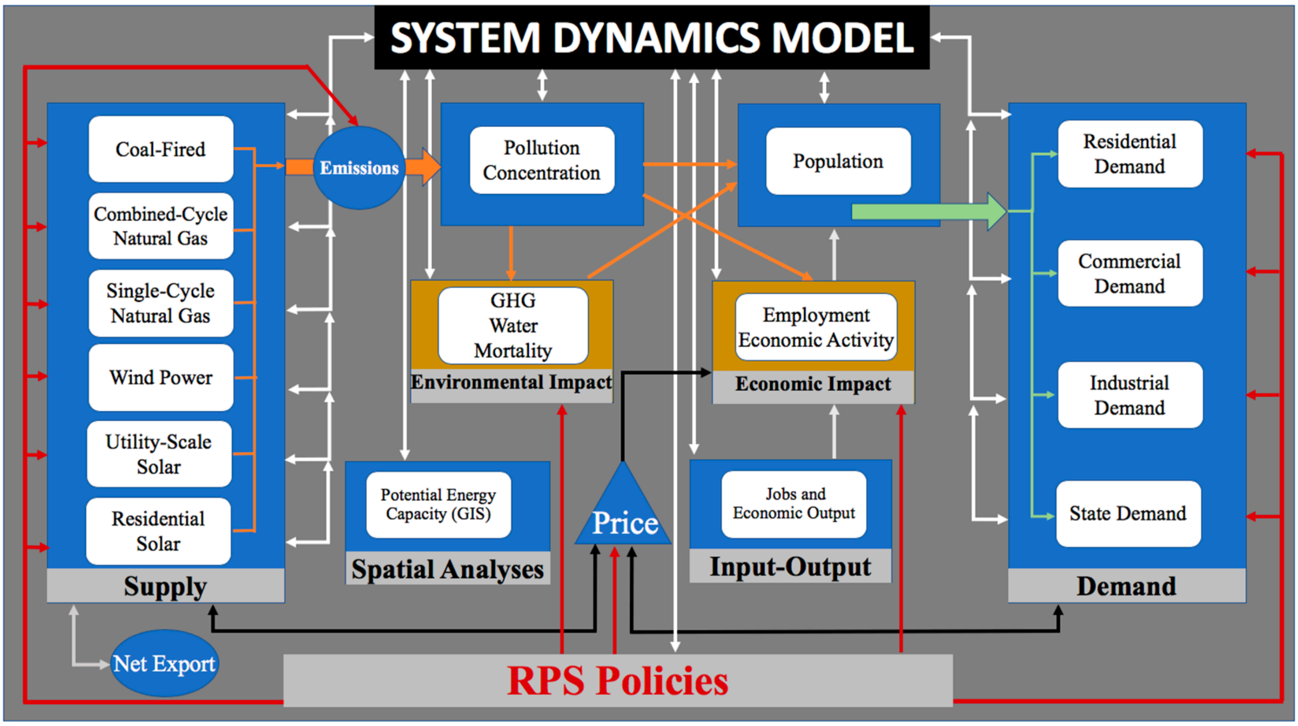


Figure 1. Modeling schematic.

The electricity market outcome at each time step maps into economic activity, estimated in dollars, which is one part of our macroeconomic module. The level of economic activity impacts the job outcome through changes in the demand for workers. It should be noted that population can also be impacted by the job impact as it could result in net out- or in-migration.

The linkage between the electricity market and the environment (potential external impacts) is represented through a pollution component, where emissions during a time step add to the concentration level of the pollutant. We depict direct impacts of pollution through impacts on economic activity and through population (e.g., health impacts). It should be noted that there are a number of potential indirect links through, for example, consumer groups. In addition to pollution, our basic model includes water resources and human and avian mortalities. Further, RPS policies are included. Depending on the policy, the generation capacity, supply, demand, market prices, emissions, economic activity, or jobs could be impacted. Finally, all of these modules and methodologies are gathered in a unique SD model. Figure 2 summarizes the causal loop diagram utilized in developing the SD model.

In order to read the causal loop diagram depicted in Figure 2, we begin by imagining the variable at the base of the arrow increasing in value; the sign at the arrowhead indicates the increase (+) or decrease (−) in the variable at the arrowhead, all other variables unchanged. Lastly, parallel lines crossing an arrow indicate delay in impact from the variable at the base of the arrow to the variable in the head of the arrow. The causal loop diagram presents the logic behind our SD model. The following is an explanation of one path in the diagram.

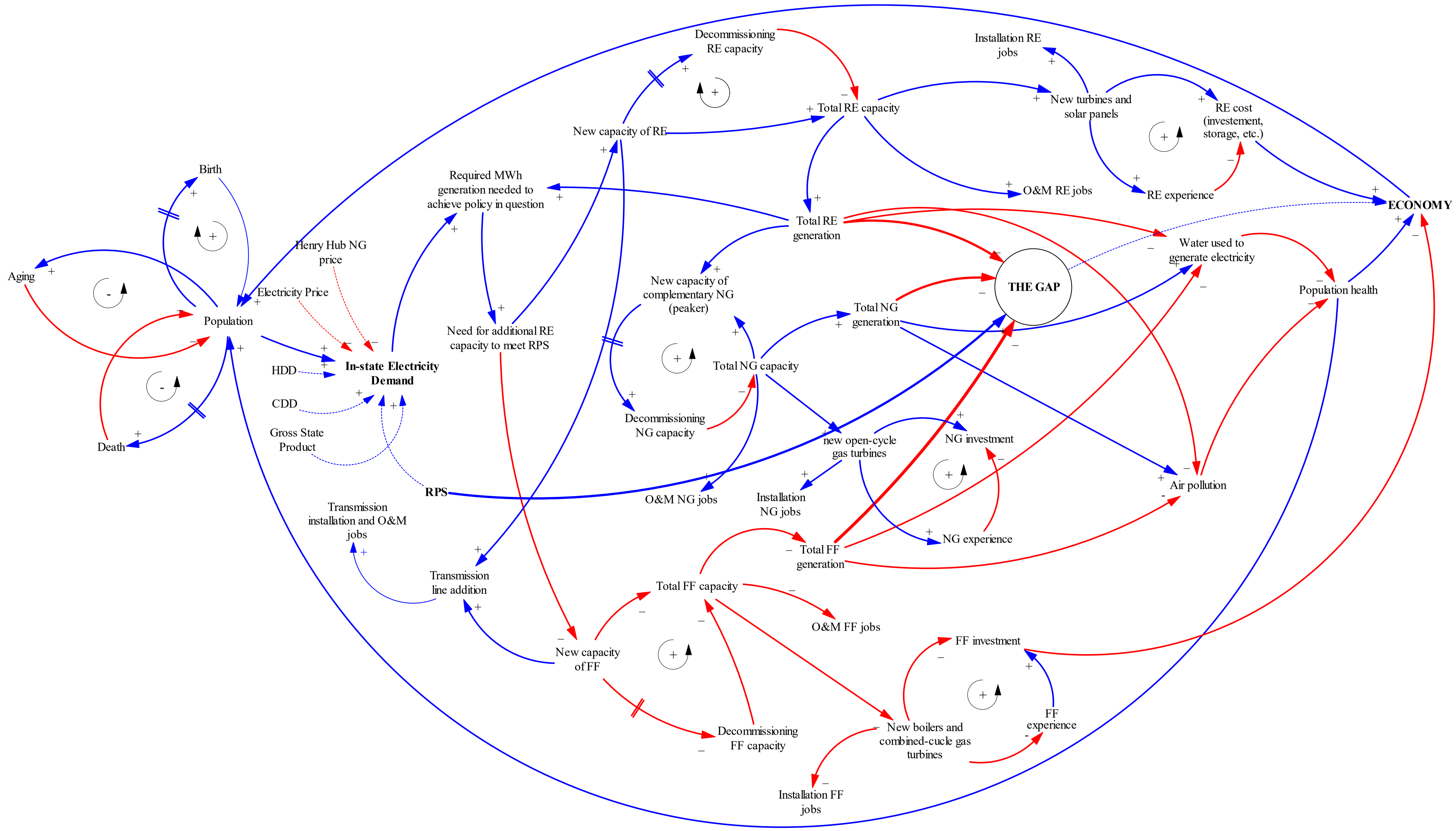


Figure 2. Causal loop diagram utilized to develop the SD model.

The required generation to achieve a certain level of RPS increases as in-state electricity demand increases, which increases the need for additional RE capacity to meet the corresponding RPS level. The higher the need for additional RE capacity, the higher the new capacity of RE. As the new capacity of RE rises, the total RE capacity rises, and the capacity that is decommissioned in the future increases with a delay. A higher level of RE capacity that is to be decommissioned decreases the total RE capacity, creating an enforcing loop (see Figure 2). On one hand, the higher the RE capacity, the higher the RE generation, hence the higher the need for peaker natural gas, storage, and transmission lines. On the other hand, if we assume that a higher level of RE generation replaces fossil fuel generation, then a higher level of RE generation results in lower GHG and air pollution, thereby lowering population mortality and morbidity (social cost). A higher level of RE generation can also decrease the gap caused by a discrepancy between supply and demand for electricity and/or RPS requirement. The same logic holds true for the remaining components of the causal loop diagram.

Data

Data were obtained from numerous sources including, the U.S. Energy Information Administration (various survey forms, AEO2018, and Layer Information for Interactive State Maps shapefiles), Emissions and Generation Resource Integrated Database (eGRID) of the U.S. Environmental Protection Agency (EPA), the National Renewable Energy Laboratories (JEDI, Annual Technology Baseline, wind data, and solar data), the New Mexico Public Regulation Commission, the United States Geological Survey, the U.S. Bureau of Economic Analysis, the United States Census Bureau, and the Western Electricity Coordinating Council, as well as the energy literature. Except for RPV data, we obtained generation data from EIA-923 and EIA-861 (annual and monthly data). The data includes historical nameplate capacity of the existing power plants, generation, power plants' locations (county and latitude/longitude), operating and planned retirement year times, and capacity factors. The data for the existing RPV capacity were obtained from the New Mexico Public Regulation Commission. Further, IMPLAN 2016 data were used to calculate jobs and output multipliers for each energy source. Lastly, economic benefit/cost of air pollution and GHG reduction multipliers came from the energy literature. Table S2 of the Supplementary Materials summarizes the key data sources.

4. Results

In this section, we present our results. We first review electricity generation under the three modeled scenarios. Next, we discuss state-level and county-level economic and environmental impacts. Economic impact results are presented for full-time equivalent employment and gross economic output. Environmental impacts, on the other hand, are reported in terms of GHG emissions, air pollution, water usage, and human and avian mortality associated with each of our three modeled scenarios. These impacts are experienced once the plants are in the O&M phase. Thus, environmental impact results are reported for the operations period solely and on a state- and county-level basis. Finally, we compare results across scenarios to expose whether results are statistically significantly different. If they are, we then identify state and county levels that experience job gains (winners) and job losses (losers).

4.1. Generation

Figure 3 shows the total electricity generation under the three modeled scenarios, and Figure 4 presents the generation mix through 2050. Based on the 20% RPS scenario, as with the other two scenarios, RE and fossil fuel generations encompassed respectively 17% and 83% of total generation in 2017. In 2030, generation shares are 15% and 85% for RE and fossil fuel, respectively. Compared to the 20% RPS scenario, RE generations are 9% higher in the generation mix under the 100% RPS scenario (24%) and 5% lower under the 10% RPS scenario (12%). All scenarios estimated a dip in electricity generation from 2036 until the end of 2037. This is due to the decommissioning of the existing coal-fired power plants in that period. The dip in the overall electricity generation is expected to be compensated by importing nuclear energy from Arizona. The figures depict generation from both within the state and not imported into the state.

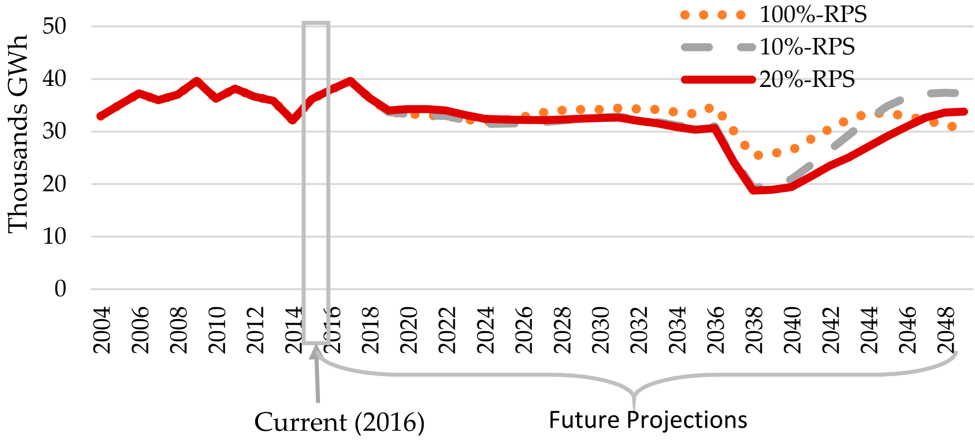


Figure 3. Total annual electricity generation under the three modeled scenarios.

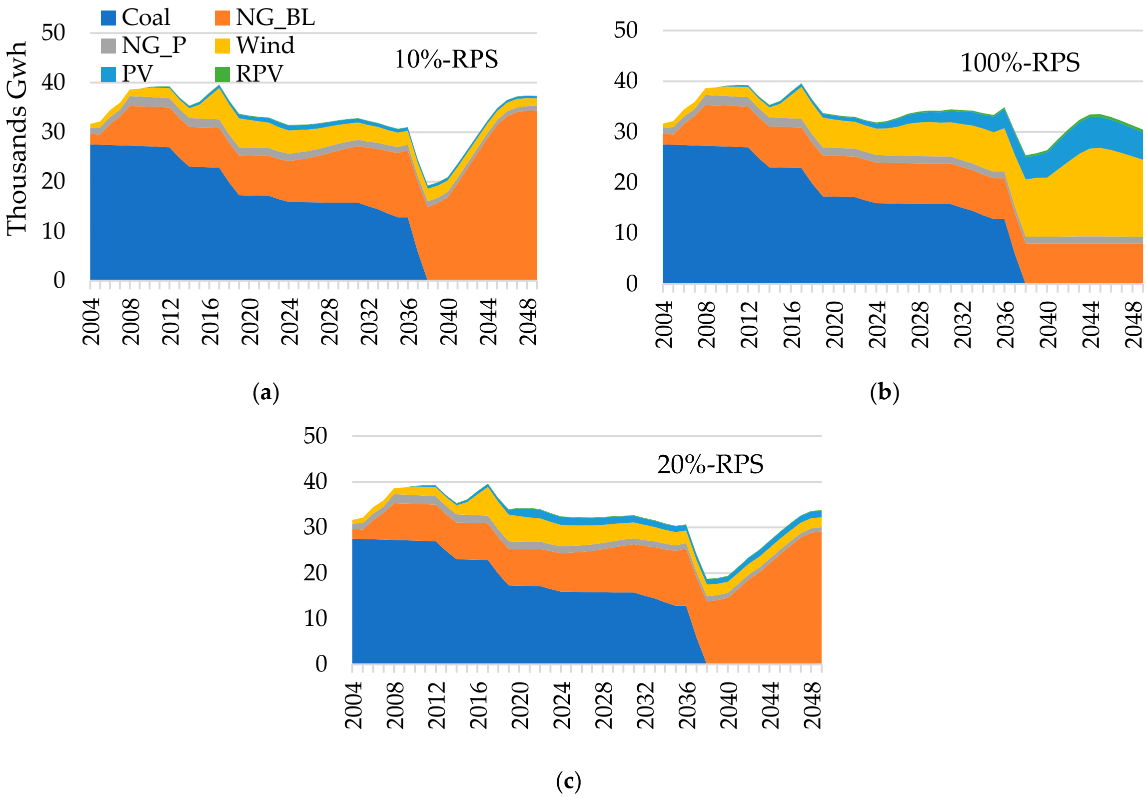


Figure 4. Annual electricity generation (in thousand GWh or TWh) by all six energy sources: (**a**) 10% RPS; (**b**) 100% RPS; (**c**) 10% RPS scenarios.

As presented in Figure 4, for the scenarios we estimated the amount and type of energy source to replace coal generation. By 2050, RE generation increases to 52%, while fossil fuel generation drops to 48% under the 20% RPS scenario. The 100% RPS scenario and the 10% RPS scenario result in a 11% higher and a 48% lower RE generation, respectively, when compared with the 20% RPS scenario. As mentioned, RPS requires utility companies to generate a portion of their in-state sales from RE. Thus, it is possible to have fossil fuel generation even under the 100% RPS scenario. The takeaway here is that different energy scenarios lead to different energy mixes, which therefore means different environmental and economic impacts.

4.2. Economic Impacts

Our model is capable of estimating employment and gross economic output by three categories: direct (onsite), indirect, and induced. Total impact is the sum of direct, indirect, and induced impacts. Since direct, indirect, and induced impacts are a fixed fraction of total impact, we only discuss total impacts here. In what follows, we first discuss employment impact at the state and county level. We then compare results across scenarios and identify whether there are winners or losers. Next, we summarize total economic output results in a similar approach. Further discussion of the results, especially more granular level results (e.g., different types of energy sources during different phases), can be found in the Supplementary Materials (Section C).

Figure 5 summarizes the cumulative total employment impact by the 20% RPS scenario and the other two modeled scenarios. We estimated a total employment impact on New Mexico in construction and O&M to be as follows: 151,857 (42,517 RE and 109,340 fossil fuel), 151,284 (112,593 RE and 38,691 fossil fuel), and 155,520 (26,271 RE and 129,248 fossil fuel) full-time equivalent jobs according to the 20% RPS, 100% RPS, and 10% RPS scenarios, respectively, from January 2017 to January 2050. Thus, compared to the 20% RPS scenario, the 100% RPS one (RE intensive scenarios) results in 573 fewer cumulative (construction and O&M) full-time equivalent jobs, while the 10% RPS one (most fossil fuel intensive scenario) yields 3663 more cumulative jobs. Note that these results are based on the assumption that all labor is provided locally. This assumption, which is on a 0–100% scale, can also be changed in the original SD model. What is important here is that this assumption does not impact the dynamics within modules and only results in lower direct economic impact (labor and economic output) across scenarios.

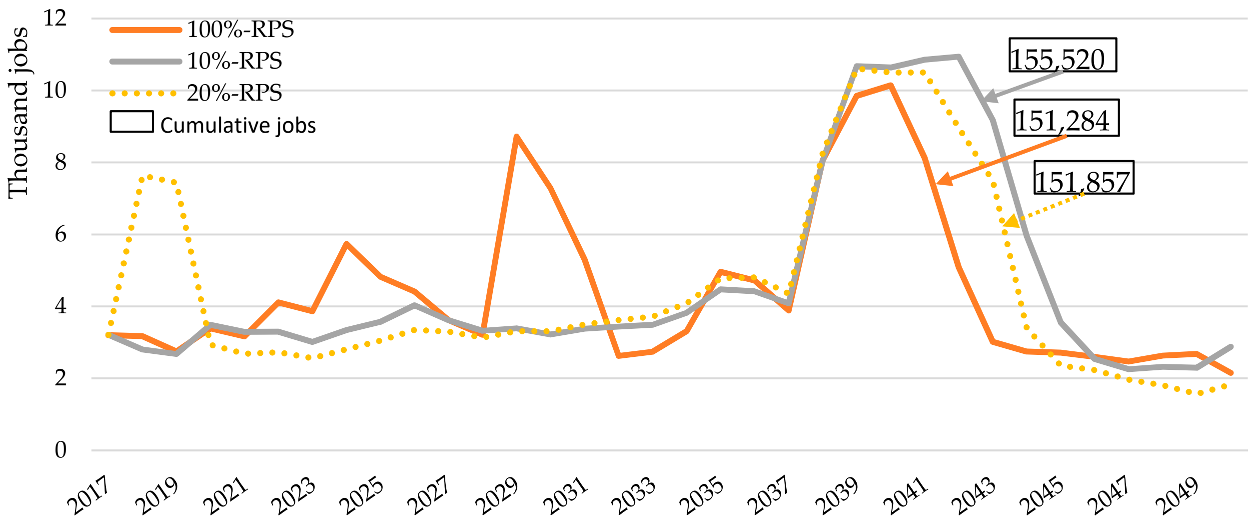


Figure 5. Temporal cumulative jobs (construction and O&M) by modeled scenarios from January 2017 to January 2050.

As demonstrated in Figure 5, all scenarios estimate a boost in energy employment after 2037. This is because existing coal-fired power plants are expected to retire in 2037, meaning there should be no new installation. Depending on the scenario, coal generation is expected to be replaced by either renewables or natural gas after 2037, and thus jobs related to coal are also likely to be replaced by renewable or natural gas jobs. Although the 100% RPS scenario yields fewer cumulative total jobs than the 20% RPS case, its impact fluctuates and is more diverse throughout the timespan of the study. Figure 3 depicts the employment distribution by the three modeled scenarios from 2017 through January 2050. Any spikes in the estimated employment numbers can be due to whether RPS and RE carveout requirements are met. We performed nonparametric tests such as the Kolmogorov–Smirnov tests to compare the equality of distributions of total employment across scenarios. The test results suggest that the null hypothesis of equality of distributions across the three scenarios cannot be rejected. In other words, at the state level, the employment impact of these three scenarios are not statistically significantly different. Thus, we found that the state of New Mexico is not a winner or a loser in terms of job gains or losses at the state level under all of the assessed scenarios. Temporal and cumulative employment impacts during construction and O&M phases are provided in the Supplementary Materials (Section C).

Now, we turn our attention to county-level employment results. Table 2 summarizes the annual average employment for all three scenarios by county. This table demonstrates an important result of the current study: some counties will be winners, and others will be losers. Figure 6 puts these results in perspective; it shows employment gain and loss per 10,000 labor force for the 100% RPS case versus the reference case of 20% RPS. Lastly, the Kolmogorov–Smirnov test results at the county level support the statistically significantly different employment distributions as well.

Table 2. Annual average employment by county and modeled scenarios *.

County	20% RPS	100% RPS	10% RPS
Bernalillo	301	83	320
Catron	22	93	3
Chaves	19	121	8
Cibola	23	118	4
Colfax	26	128	6
Curry	211	275	188
De Baca	23	94	3
Dona Ana	397	225	393
Eddy	285	121	289
Grant	284	119	291
Guadalupe	44	132	24
Harding	23	115	3
Hidalgo	294	120	300
Lea	536	443	498
Lincoln	7	45	3
Los Alamos	41	31	35
Luna	442	334	419
Mc Kinley	303	67	325
Mora	23	126	3
Otero	16	114	6
Quay	79	160	59
Rio Arriba	23	112	3
Roosevelt	137	210	117
Sandoval	39	58	34
San Juan	764	569	762
San Miguel	23	110	4
Santa Fe	12	35	7
Sierra	22	108	3
Socorro	22	108	3
Taos	23	97	3
Torrance	155	235	136
Union	81	163	61
Valencia	306	84	322

* Average values are from 2017 to 2050.

Economic output follows the employment results closely: when there is employment impact, there is economic output impact as well. Construction and O&M employees, depending on type of energy source, earn an average annual salary (with benefit) of 35,000 to 58,000 USD (2017$) and 56,000 to 76,000 USD (2017$) per year, respectively [36]. Under the 20% RPS scenario, these employments result in a cumulative (sum of construction and

O&M) total economic output of 24 billion USD (2017$) (18% RE and 49% O&M) per year from 2017 to 2050. The 100% RPS and 10% RPS scenarios respectively lead to roughly 4 (20 USD: 94% RE and 54% O&M) and 2 (22 USD: 4% RE and 45% O&M) billion USD (2017$) per year less than the 20% RPS case. In other words, the 20% RPS scenario yields a cumulative economic output that is 20% and 9% higher than the 100% RPS and 10% RPS scenarios, respectively. Figure 7 summarizes these results.

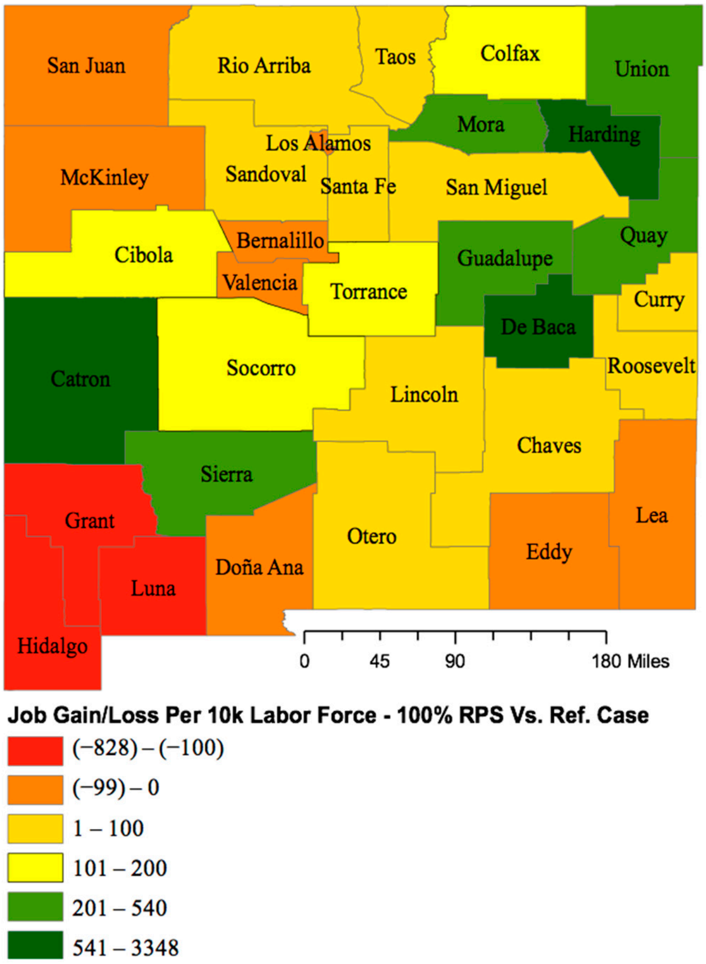


Figure 6. Employment gain and loss per 10,000 labor force under the 100% RPS case compared to the 20% RPS case. Note: Positive values indicate job gains; negative values are job losses.

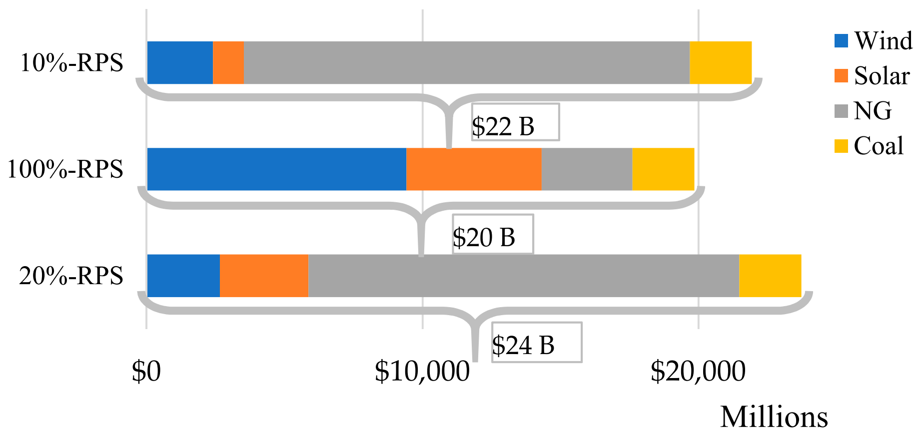


Figure 7. Total annual economic output by energy source and modeled scenarios from 2017 to 2050.

Similar to the state-level employment, economic impact distributions under the three assessed scenarios are not statistically significantly different. However, at the county level, rural counties can benefit under the RE intensive scenario, and counties with fossil fuel infrastructure in place can benefit from the fossil fuel intensive scenarios (namely the more populous counties).

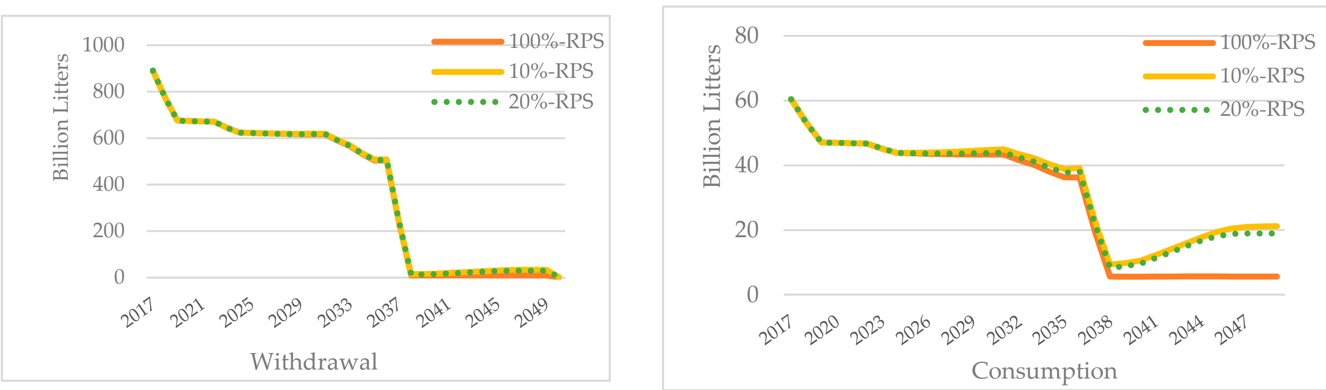
4.3. Environmental Impacts

Based on all of the three modeled scenarios, coal-fired power plants are assumed to fully retire after 2037. This is mainly due to the fact that the existing coal-fired power plants are aging (>40 years), and fuel contracts with coal mines are ending; more importantly, it is highly likely that coal will no longer be cost-competitive. Given these situations, we expect that there would be no new coal-fired power plants constructed in the future (see Figure 4). Note that these power plants are the most water-intense and polluting technologies in our set of energy sources (see Table S6). Eliminating coal from New Mexico's energy mix would result in fewer negative externalities (GHG, ambient pollutions, and water usage) from fossil fuel overall. Different technology costs along with RPS requirements drive the energy source that would eventually replace coal. The more RE replaces coal, the fewer negative externalities and the higher the social benefit from the replacement.

In what follows, we first discuss cumulative water withdrawal and consumption results at the state and county level. We then compare results across scenarios and identify whether there is water saved at the state and county levels. We take a similar approach in explaining emissions. Finally, we discuss the social benefit/cost of different scenarios.

4.3.1. Water Usage

Figure 8 depicts the temporal water withdrawal and consumption from 2017 to 2050. The 20% RPS scenario suggests a cumulative 13,178 and 1096 billion liters of water withdrawal and consumption throughout the study timeline. Compared to the 20% RPS scenario, the 100% RPS scenario uses less water for withdrawal and for consumption by 190 and 122 billion liters, respectively. The 10% RPS scenario, with the highest level of fossil fuels in the energy mix, uses 41 and 26 billion liters of water more than the 20% RPS scenario for water withdrawal and consumption, respectively.



(**a**) (**b**)

Figure 8. Water withdrawal and consumption over time by the electric sector under the three modeled scenarios. (**a**) Water withdrawal; (**b**) Water consumption.

Considering an average price of 0.00689 USD/liter for water consumption by each energy source [37], the 20% RPS scenario results in a total cost of 527 million USD ($2017) in water consumption for electricity generation. Compared to the 20% RPS scenario, the 100% RPS scenario results in saving 58 million USD for water savings, while the 10% RPS scenario increases costs by 13 million USD, as it is more water intense.

To compare water consumption distributions across scenarios, we performed Kolmogorov–Smirnov tests. Test results provided us with evidence to reject the null hypothesis of equality of distributions between the 100% RPS and 20% RPS scenarios even at the state level. On the whole, we did not find similar results when comparing the 10% RPS scenario against the 20% RPS one.

Table 3 summarizes the annual average million liters of water consumption by county and the three scenarios; Figure 9 translates this information to per capita (county) water consumption saved or lost. While the majority of counties see no changes, the majority of impacts are the savings. Our nonparametric test results further support the alternative hypothesis of unique water consumption distributions across scenarios at the county level.

Table 3. Annual average water consumption by county and modeled scenarios *.

County	20% RPS	100% RPS	10% RPS
Bernalillo	46	16	53
Catron	0	0	0
Chaves	0.08	0.68	0.04
Cibola	0	0	0
Colfax	0.23	0.23	0.23
Curry	0	0	0
De Baca	0	0	0
Dona Ana	119	89	126
Eddy	31	1	38
Grant	34	4	41
Guadalupe	0	0	0
Harding	0	0	0
Hidalgo	39	8	45
Lea	217	187	223
Lincoln	0	0	0
Los Alamos	13	7	14
Luna	140	109	146
Mc Kinley	203	173	209
Mora	0	0	0
Otero	0.08	0.68	0.04
Quay	0	0	0
Rio Arriba	0	0	0
Roosevelt	0.08	0.68	0.04
Sandoval	0	0	0
San Juan	1873	1843	1879
San Miguel	0	0	0
Santa Fe	0.08	0.68	0
Sierra	0	0	0
Socorro	0	0	0
Taos	0	0	0
Torrance	0	0	0
Union	0	0	0
Valencia	50	20	56

* Average values are in million liters and from 2017 to 2050; "0" means no change.

4.3.2. Air Pollution and Greenhouse-Gas Emissions

Figures 10 and 11 depict the cumulative impact of air pollution and GHG emissions, along with consecutive social benefit to the state from 2017 to 2050. Cumulatively, the RE intensive scenario emits roughly 91 million tonnes GHG less than the 20% RPS scenario throughout the study timeline, leading to more than 6.8 billion USD (2010$) in cumulative climate benefit. The fossil fuel intensive scenario, on the other hand, emits 3% (19 million tonnes) higher GHG than the 20% RPS one, which causes more than 1400 million USD (2010$) social cost compared to the 20% RPS one. Each one million tonnes of GHG emissions is equivalent to GHG emissions by approximately 2250 million miles driven by an average passenger vehicle. Table 4 summarizes the county level results only for GHG. Based on the Kolmogorov–Smirnov test results, we can reject the null hypotheses of equality of GHG emission distributions when comparing both the 100% RPS and 10% RPS scenarios against the 20% RPS scenario. In other words, the 100% RPS scenario results in statistically significantly lower GHG than the 20% RPS scenario, while the opposite holds true for the 10% RPS scenario. We found similar results at both state and county levels.

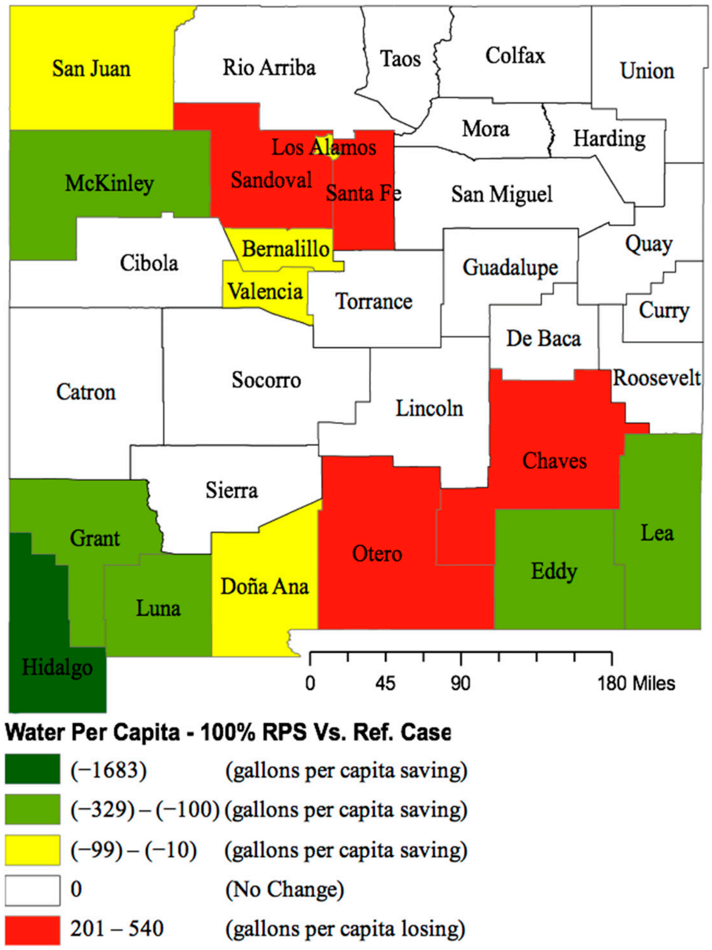


Figure 9. Per capita water consumption saved/lost under the 100% RPS scenario compared to the 20% RPS scenario. Note: Negative value indicates water saved; 1 gallon is ≈3.79 liters.

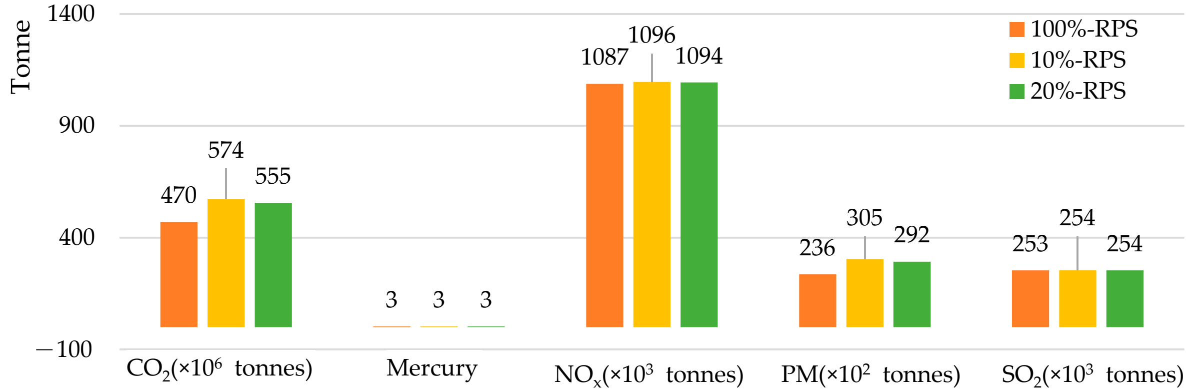


Figure 10. State-level cumulative tonnes of GHG and air emission under the three modeled scenarios from 2017 to 2050.

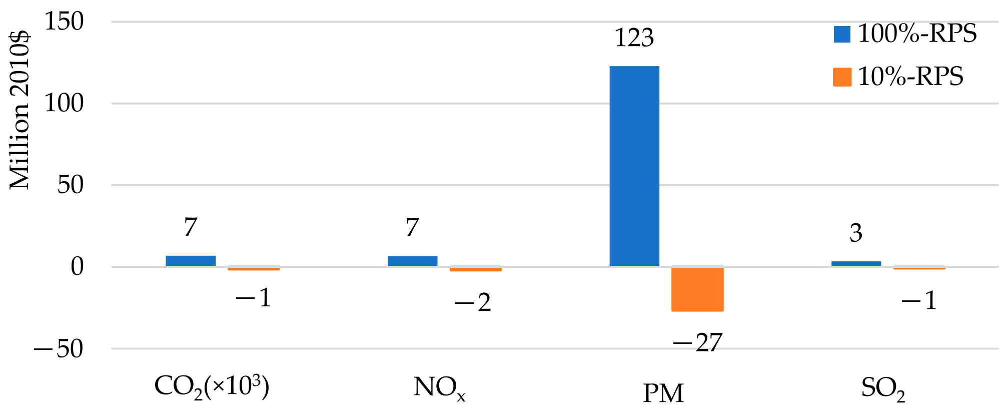


Figure 11. Social impact of air pollution and GHG emission reduction for the 100% RPS and 10% RPS scenarios compared to the 20% RPS scenario from 2017 to 2050.

Table 4. Annual average thousand tonnes of GHG emissions by county and modeled scenarios.

County	20% RPS	100% RPS	10% RPS
Bernalillo	38	18	43
Catron	0	0	0
Chaves	0.09	0.78	0.02
Cibola	0	0	0
Colfax	0.24	0.24	0.24
Curry	0	0	0
De Baca	0	0	0
Dona Ana	90	69	95
Eddy	23	1	27
Grant	26	4	31
Guadalupe	0	0	0
Harding	0	0	0
Hidalgo	32	10	36
Lea	160	139	165
Lincoln	0	0	0
Los Alamos	9	5	10
Luna	101	79	105
Mc Kinley	93	71	97
Mora	0	0	0
Otero	0.09	0.78	0.02
Quay	0	0	0
Rio Arriba	0	0	0
Roosevelt	0	0	0
Sandoval	0.09	0.78	0.02
San Juan	785	764	790
San Miguel	0	0	0
Santa Fe	0.09	0.78	0.02
Sierra	0	0	0
Socorro	0	0	0
Taos	0	0	0
Torrance	0	0	0
Union	0	0	0
Valencia	45	23	49

Note: Average values are in thousand tonnes and from 2017 to 2050; "0" means no change.

Since coal is the only energy source that emits mercury and since it stays unchanged throughout our study period, mercury is therefore assumed to be the same amount in all three scenarios, i.e., 3 tonnes. The 100% RPS scenario results in a roughly 500 tonne reduction in SO_2 emissions (approximately 3 million USD (2010$) in social benefit) compared to the 20% RPS scenario, while the 10% RPS scenario results in an increase of more than

100 tonnes of SO_2 (1 million USD (2010$) in social cost) cumulatively from 2017 to 2050. NO_x emissions in the RE intensive scenario are reduced by 6649 tonnes and a 7 million USD (2010$) increase in social benefits compared to the 20% RPS scenario, while the fossil fuel intensive scenario yields 1990 tonnes more NO_x and 2 million USD (2010$) more in social costs. Lastly, PM emission in the 100% RPS scenario is reduced by 5612 tonnes, resulting in a 123 million USD (2010$) increase in social benefits compared to the reference case scenario, while the 10% RPS scenario yields 1215 tonnes more and 27 million USD (2010$) in social costs.

Table 5 summarizes the cumulative avoided air pollution, social benefit, and the premature mortality and morbidity impact of air pollution under the 100% RPS and the 10% RPS scenarios from 2017 to 2050 compared to the 20% RPS scenario. The 20% RPS scenario is estimated to have 408 to 924 adult fatalities caused by a combination of SO_2, NO_x, and PM pollutants. The 100% RPS scenario has the potential to avoid 23 to 52 premature mortality incidences, while the 10% RPS scenario increases 5 to 11 fatalities due to exposure to ambient pollution, when compared to the reference scenario. While the majority (>90%) of social benefits for each scenario comes from avoiding premature mortality [12], we also estimated a number of additional morbidity benefits, from avoiding nonfatal heart attacks, hospital visits for asthma, or other cardiopulmonary conditions, to fewer lost work or school days. For example, the 100% RPS scenario is estimated to result in avoiding 19 visits to the emergency department or hospital for cardiopulmonary conditions as well as approximately 3000 fewer lost work or school days from 2017 to 2050.

Table 5. Accumulated emissions, social benefits, and mortality and morbidity incidence reductions compared to the reference case scenario (20% RPS) using SO_2, NOx, and PM reductions as a result of RE installation from 2017–2050.

Outcome	100% RPS			10% RPS			20% RPS		
	SO_2	NO_x	PM	SO_2	NO_x	PM	SO_2	NO_x	PM
Emission Reductions (Thousand Tonnes)									
	0.45	6.7	5.7	−0.1	−2	−1.2	*254*	*1094*	*29*
Social Benefits (2010 million USD)									
	3.4	6.6	122.8	−0.7	−2.0	−26.6	*1928*	*1078*	*640*
Premature Mortality Incidences									
Krewski et al. [13] [a]	0	1	22	0	0	−5	*207*	*95*	*107*
Lepeule et al. [14] [a]	1	2	50	0	0	−11	*464*	*219*	*241*
Morbidity Incidences									
Emergency department visits for asthma	0	0	7	0	0	−1	*81*	*37*	*36*
Acute bronchitis	1	2	36	0	0	−8	*372*	*251*	*181*
Lower respiratory symptoms	9	20	464	−2	−6	−100	*4699*	*3178*	*2312*
Upper respiratory symptoms	13	29	679	−3	−9	−146	*6735*	*4540*	*3334*
Minor restricted-activity days	319	643	16,682	−69	−193	−3586	*169,722*	*99,043*	*82,791*
Lost workdays	54	110	2782	−12	−33	−600	*28,485*	*16,673*	*13,975*
Asthma exacerbation	5	1892	630	−2	−522	−156	*5900*	*226,256*	*3938*
Hospital admissions, respiratory	0	0	5	0	0	−1	*48*	*20*	*24*
Hospital admissions, cardiovascular	0	0	6	0	0	−1	*61*	*26*	*30*
Nonfatal Heart Attacks Incidences (Age > 18)									
Peters et al. (2001) [b]	0	1	22	0	0	−5	*202*	*85*	*105*
Pooled estimate of 4 studies	0	0	2	0	0	−1	*22*	*9*	*11*

Note: Positive value means reduction, whereas negative value indicates addition. [a,b] Multipliers from these studies are used to calculate the mortality and morbidity incidences.

Fossil fuel and RE power plants are contributors to avian mortality; fossil fuel plants induce fatality through plant operation, acid rain, mercury, and climate change, while bird fatality associated with wind and PV power plants is mainly due to bird colliding with turbine blades and panels respectively [15,38,39]. Figure 12 summarizes avian mortality caused by different energy sources (i.e., coal, NG, wind, and PV) under different scenarios. The 20% RPS scenario leads to 5.131 million avian fatalities, of which fossil fuel is responsible for approximately 99% of the overall number of deaths. Compared to the 20% RPS scenario, the 100% RPS scenario has the potential to save 441 thousand deaths, while the 10% RPS scenario leads to 106 thousand more avian fatalities. Lastly, the RE intensive scenario leads to more than 4.69 million bird deaths, with fossil fuel sources being responsible for 97% of the overall number.

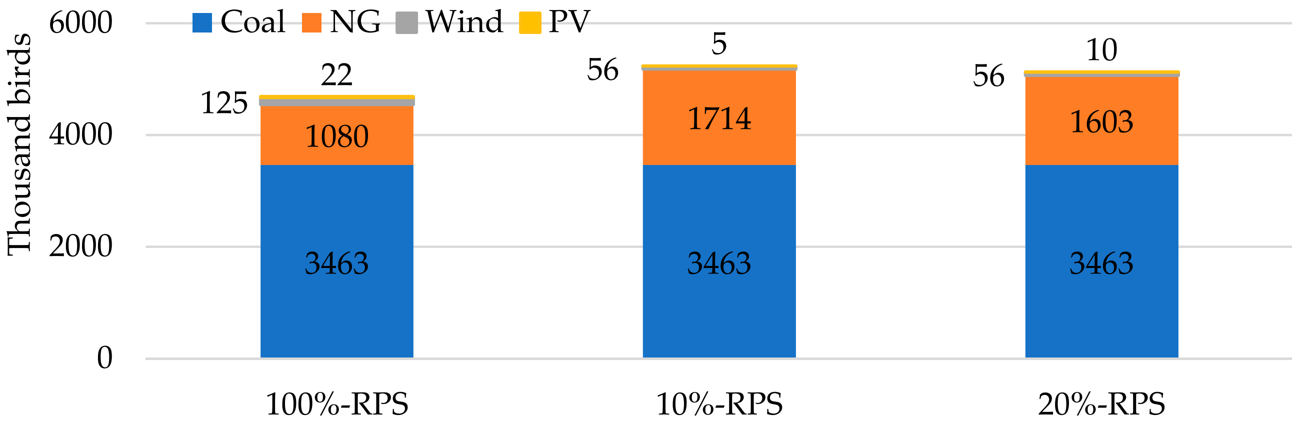


Figure 12. Avian mortality caused by coal, NG, wind, and PV power plants under the three modeled scenarios from 2017 to 2050.

Dissanayake and Ando [40] conducted a choice experiment survey in Illinois and found that their respondents are willing to pay between 1.11 and 1.13 USD for each extra bird per year, and between 7.72 and 10.22 USD for each endangered species annually. Since we were unable to discern different types of birds (generic versus endangered species) in our analysis, we utilized the mean value of the upper-level estimates as to how much each bird death is worth. We estimated that the 100% RPS scenario is capable of saving 3 million USD in bird mortality, while the 10% RPS scenario costs the state 1 million USD more in avian mortality, when compared with the 20% RPS scenario. We performed Kolmogorov–Smirnov tests and *t*-tests on human and avian mortality, and also on air pollutants (except mercury), and we found similar results to those of GHG and water consumption.

4.4. Summary of Cumulative Results

Our analysis seeks to investigate the economic and environmental impacts of the status quo scenario, along with two future scenarios. Without considering environmental impacts such as water usage, air pollution, GHG, and avian mortality, our results suggest that the reference case and the fossil fuel intensive scenarios lead to higher economic output and total employment impacts than the RE intensive scenario, though not statistically significant. Once the environmental impacts are included, these results no longer hold. Compared to the 20% RPS scenario, cumulatively, the 100% RPS scenario results in 3095 million USD (2017$) higher benefit and the 10% RPS scenario in 3325 million USD (2017$) more cost to the state. This makes the 100% RPS the best scenario, 20% RPS the second best, and 10% RPS the worst-case scenario, when both environmental and economic impacts are taken into account. Thus, the higher the RPS level, the higher the overall benefit to the state. Table 6 summarizes the state cumulative results in relation to the 20% RPS scenario. At the county level, compared to the 20% RPS case, we found that RE suitable counties are net gainers (in terms of both economic and environmental impacts), while fossil fuel counties suffer economically and benefit environmentally under the 100% RPS scenario. The opposite holds true when comparing the 10% RPS scenario against the 20% RPS scenario.

Table 6. Summary of cumulative results in relation to the 20% RPS scenario from 2017–2050.

Outcome	100% RPS, in Million USD	10% RPS, in Million USD
Economic Output	−3962 (−120)	−1881 (−57)
Water benefit	59 (2)	−13 (−0.4)
CO_2	6865 (208)	−1402 (−42)
SO_2	3 (0.1)	−1 (−0.03)
NO_x	7 (0.2)	−2 (−0.1)
PM2.5	123 (4)	−27 (−1)
Bird mortality	+3 (0.1)	−1(−0.03)
Total monetary value	3095 (94)	−3325 (−101)
Employment value [a]	−180 (−5)	+328 (10)

Numbers in parentheses are annual values. [a] Employment monetary values are based on salary of 46,500 USD for construction and 66,000 USD for O&M jobs [36], calculated based on the employment count (see Section 4.2) of −573 (−17 annual) jobs and 3663 (111 annual) jobs for the 100% RPS and 10% RPS scenarios, respectively.

5. Conclusions and Policy Implications

Legislators across the globe are supporting policies that move toward electricity generation from renewable resources. To this end, some jurisdictions in the U.S. have enacted regulations, such as the RPS. These provide a mechanism that can result in not only GHG emission reduction but also water preservation. This is especially prudent in geographic locations with limited water resources. Moreover, RPS can support jobs, although the primary policy target of an RPS is not focused squarely on job creation.

This study provided a roadmap of how to quantify the economic and environmental impacts of three scenarios, in which not only the RPS level varies but also the energy sector dynamics, technological cost, and price of energy. Specifically, we modelled New Mexico's newly enacted RPS policy, where it increases from the status quo of 20% by 2020 to 100% by 2050. We also studied a scenario where RPS decreases to 10% by 2050. In so doing, we combined results from input–output (JEDI and IMPLAN) analyses, econometrics (Stata), and GIS (ArcGIS), and we created a unique SD model that enabled us to assess regional economic and environmental impacts of different scenarios. Our contribution to the current body of literature is twofold: not only did we assess different RPS scenarios by considering the underlying dynamics within the energy sector, but we also assessed these impacts at a lower granular level (i.e., county level).

Under the status quo scenario, the estimates in our model accounted for 152 thousand cumulative full-time equivalent jobs, 24 billion USD in economic output, 3648 million USD in air quality cost, 36 billion USD in climatic cost, 527 million USD worth of water use, 5 million avian mortality, and 409–924 premature mortality. Compared with this status quo scenario, our analysis suggests that the RE intensive scenario (100% RPS) leads to less cumulative employment and economic output, but much higher social benefits compared to the 20% RPS scenario, i.e., 500–15,000 fewer cumulative jobs, 3–4 billion USD less in cumulative economic output, 132 million USD less in air quality cost, 7 billion USD less in climatic cost, 58 million USD less in value of water use, 441–485 thousands less in avian mortality, and 23–53 less in premature mortality. The 10% RPS scenario leads to approximately 4000 more jobs, 2 billion USD less in cumulative economic output, 29 million USD more in air quality cost, 1 billion USD more in climatic cost, 13 million USD more in value of water use, 100 thousand more in avian mortalities, and 5–11 more in premature mortality than the 20% RPS scenario. Considering the environmental impacts, our analysis finds that the Senate Bill RPS scenario (100% RPS) is the best scenario, followed by the status quo scenario, and the 10% RPS scenario is the worst case.

Higher levels of RPS policy aligns with support from New Mexicans. In separate work by the co-authors [41,42], we estimated that a sample of New Mexicans are willing to pay 5.4 USD per year on top of their annual electricity bill for each 1% increase in the current level of RPS (20%). To achieve a 100% RPS by 2050, we extrapolate that, all else equal, New Mexicans are willing to pay 58, 180, 373, 581, 803, and 1144 million USD (2017$) in 2020, 2025, 2030, 2035, 2040, and 2050, respectively. Note that the wide range of willingness to pay is due to the way the bill requirements of achieving 80% RPS by 2040 were designed. Under this bill, electric utility companies were required to increase current RPS level to 25% by 2020, 35% by 2025, 50% by 2030, 65% by 2035, and 80% by 2040. The higher the percentage, the higher residents are willing to pay.

Although scenarios with a lower level of RPS might result in supporting a higher number in employment (in the fossil fuel sector), these scenarios lead to much higher social cost of GHG and ambient pollution (i.e., premature mortality and morbidity) and water usage. This suggests that coming up with an overarching policy that benefits both the environment and economy is not an easy task. Policymakers seeking to promote energy policies may need to consider not only the economic benefit associated with energy development but also social welfare. In other words, RPS policies are more desirable when internalizing external costs and hence correcting for market failure [21,43,44].

Further, the most decisive conclusion that can be drawn from job comparison across different scenarios is that the higher the RE development level, the more disperse and rural the employment impact. On the contrary, the higher the level of fossil fuel deployment, the less diverse and rural the job impact. San Juan County among all is expected to experience a net negative (loss) in O&M jobs, i.e., a loss of 780 jobs from coal-fired power plant retirements after 2037 and depending on the scenario, a gain of an annual average of 84 (100% RPS) to 601 (10% RPS) jobs. Concurrently, the state is estimated to experience nearly 686 billion USD (100% RPS) in social benefits, particularly from the coal power plants retirement. The disparity in job and economic output distribution across counties and energy sources suggests that counties with varying energy potential and population density may experience variation in impacts. In other words, some counties are likely to be net gainers while others may suffer.

The results of this study are broadly consistent with that in the literature [20,26,29,45–49]. We do recognize that the majority of these studies had explicit research questions only on wind energy. For example, some studies sought to measure the actual economic impact of a particular wind installation at county level (e.g., [48]), while others estimated a wind vision for the U.S. (e.g., [26,49]) or the environmental and economic impact of RPS policies nationwide for solely one year (i.e., [20]). Similar to Barbose et al. [20], Millstein et al. [29], and Wiser et al. [21], our model suggests that RPS policies have the potential to yield billions of dollars in climatic and air-quality benefits as well as economic benefits. Similar to preceding studies, we found that increasing RPS does not result in stimulating the economy of a state [3,4], but it does impact the environment positively [29,45,50]. Our contribution to the literature is that we demonstrated that increasing RPS does stimulate the economy of the state at the more granular levels (especially rural counties).

The tools and theories integrated for the analysis in this research are broadly transferable across a wide range of topics and/or regions. For example, a similar approach can be taken to evaluate RPS policies in each one of the other 28 states with such regulations. Our model can be modified and used for states with existing 100% RPS policies (Hawaii, California, Washington, Maine, New York, and Virginia), and those with promises for 100% clean electricity (Colorado, Connecticut, Massachusetts, Illinois, Oregon, New Jersey, Nevada, Wisconsin, and Puerto Rico). Additionally, our state-of-the-art modeling and set of methods are applicable to other topics, such as the impact of decarbonization through a battery of smart grid (e.g., smart meter), transportation (e.g., electric vehicle), and energy-efficient buildings; 100% RE for all sectors (i.e., electricity, heating/cooling, transportation, and industry); oil and natural gas extraction; and the agriculture sector on regional economies. Another expansion of this analysis could include developing nations, as well as other developed countries with similar regulatory mandates. One potential limitation of this work is that our model does not calculate electricity rates for each scenario and takes rates as independent. More expensive scenarios could potentially result in higher electricity rates, which can impact economic activity. This is also important as it has the potential to impact customers' perspective and willingness to pay towards higher level of RE diffusion. Another caveat is that we assume that employment impacts are fully provided (100%) by local residents, which is not typically the case in real-world settings; although the model is capable of varying this assumption, we chose not to include this here for the purpose of brevity. Future research should account for data uncertainty and present results as confidence intervals rather than precise values. This can be done by using Monte-Carlo simulations. This study's results provided improved information for state policymakers seeking to alter RPS policies and can also be extrapolated to states with similar energy policies.

Supplementary Materials: The following will be available online at www.jamalmamkhezri.weebly.com/research.html.

Author Contributions: J.M.: Conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, resources, software, validation, writing—original draft preparation; L.A.M.: methodology, software, validation, formal analysis, writing—review and editing; J.M.C.: conceptualization, supervision, resources, funding acquisition, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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Abbreviations

Abbreviation	Definition
AEO	Annual Energy Outlook
eGRID	Emissions and Generation Resource Integrated Database
EIA	Energy Information Administration
EPA	Environmental Protection Agency
GHG	Greenhouse-gas
IMPLAN	Impact Analysis for Planning
JEDI	Jobs and Economic Development Impact
MWh	Megawatt-hour
NGp	Peaker Natural Gas
NGb	Baseload Natural Gas
NREL	National Renewable Energy Laboratory
O&M	Operating and maintenance
PV	Utility-scale photovoltaic solar
RE	Renewable energy
RPS	Renewable portfolio standards
RPV	Residential photovoltaic solar
SD	System dynamics

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Article

Comprehensive Benefit Analysis of Port Shore Power Based on Carbon Trading

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Abstract: The concept of "oil to electricity" is crucial for expanding the share of electricity in final energy consumption as well as for encouraging energy efficiency and emission reduction. Initially, a multidimensional strategy analysis is conducted for the government, ports, and ships concerned. From an economics perspective, a mathematical model of electricity substitution benefit analysis based on multiagent cooperative game theory under cap and trade and carbon tax policies is constructed, and the effect of carbon emissions caused by ships on the environment and society is converted into economic value. How several variables, such as transformation costs, ship electricity consumption, subsidy rates, carbon tax prices, and the ratio of shore power usage time to berthing time, affect the functioning of shore power is analyzed. The best electricity price under various circumstances is determined while considering the benefits of the three parties to maximize social welfare. The reduction in carbon dioxide and pollutant emissions is calculated. Meanwhile, the environmental advantages of the "replacement of oil with electricity" procedure are estimated. An example supports the claim that the suggested modeling approach can successfully resolve the economic benefits of each participant for the period that fosters the growth of electricity replacement projects and offers a sound scientific foundation for the formation of pertinent legislation.

Keywords: carbon trading; cooperative game; pollutant emission; shore power

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1. Introduction

Seaborne trade stalled in 2020 amid the COVID-19 epidemic and the anticipated downturn in global economic growth. Surveys conducted by UNCDAT have revealed that the world container throughput declined by 1.2% to 815.6 million 20-foot TEUs [1]. Governments advocated for citizens to stay inside to prevent contact, which tremendously accelerated the rise of international e-commerce. The distribution of vaccines has slowed the epidemic's growth and deaths, enabling the recovery of international trade. The beginning of the economic recovery was heralded in 2021, with seaborne trade predicted to increase by 4.3% [2]. The maritime sector's quick ascent has resulted in significant emissions of pollutants such as CO_2, SO_2, and NO_x. As of 2012, shipping was responsible for 972 million tons of greenhouse gas release, or 2.5% of all releases worldwide [3]. It not merely raises the global temperature but also leads to respiratory illnesses in those who live close to ports and coastlines [4]. There is a consensus among experts that 60% to 90% of the diffusion in ports stems from ships, which also account for 70% of marine diffusion [5].

Several nations and international organizations are pursuing numerous explorations and research to lessen the issue of pollution discharge from ships. Based on the "IMO 2020" guideline, ships operating outside specified emission-control areas can diminish sulfur oxide outflow by 8.5 million tons while exploiting low-sulfur oil with a sulfur content of 0.50% m/m [6]. More than 570,000 residents will die prematurely if the SO_x limit reduction is postponed from 2020 to 2025 [7]. Even though low-sulfur oil modestly reduces NO_x discharge by 10% [8], the maritime industry still contributes to 250,000 fatalities [9]. The usage of shore power minimizes pollution emissions by 94–97% when berthing at the port [10]. It satisfies fundamental needs such as lighting, cooling, and communication, notably improving air quality [11], decreasing carbon emissions by 800,000 tons, and elevating environmental benefits [12,13].

The present literature on shore power is confined and centers especially on technology [14,15], economy [16,17], management [18,19], policy promotion [20], etc. One study by Qi [8] observed the trend in obstacles to the upgrading of shore power in China, focusing on the economic evaluation for different stakeholders. Zhao [21] considered the effects of port size, fines, and subsidies on the evolutionary game to analyze the financial relationship between the government and the port. A mathematical model was constructed by Wu [22] to investigate how government subsidy schemes might help shorten the outflow from ship berths. Song [23] set up four parties, the government, the port, the ship, and the power grid, then pondered the cost-effectiveness of each in the shore power system to calculate the optimal shore power price. Through quantitative evaluation, Tseng [24] demonstrated that environmental policies levying pollution taxes can immensely suppress pollutant discharge.

The global community has agreed on limiting carbon emissions since the "Kyoto Protocol" took effect. On the one hand, developed nations such as the European Union, Japan, and Australia were the first to adopt cap-and-trade and carbon tax policies, which victoriously decreased CO_2 emissions [25]. On the other hand, China pledged to achieve carbon neutrality by 2060 at the 75th UN General Assembly. However, there are few surveys on the carbon trade mechanism of shore power, and the majority of studies concentrate on economic factors. Murray [26] discovered the carbon price legislation lowered British Columbia's emissions by 5–15% through modeling. The EU Emissions Trading Scheme's implementation has resulted in a 0.5–2 million ton CO_2 reduction [27]. Song [28] developed a stochastic model to explore the effects of various carbon tax rates on the growth of logistical capacity. A dual-objective optimization model was developed by Liu [29] to discuss the liner's best performance under the carbon tax policy. Chen [30] described a social optimal welfare model to assess how carbon taxes affect production, consumption, and redistribution.

This study uses multiagent game behavior as its research object in the "oil-to-electricity" conversion process. Economically speaking, the government, the port, and the ship are strategically examined, and the cost of the port includes the value of the carbon. The whole social welfare is maximized by the favorable shore electricity price. The environmental advantages of "oil-to-electricity" are counted simultaneously.

2. Electricity Substitution Multiagent Game Model

2.1. Multiagent Game Analses

Figure 1 depicts the evolution of port shore power based on a cooperative game. Due to the contradictory objectives being sought by the government, port, and ships while replacing electricity, a game of interests has developed.

Ships consuming fuel oil pollute the environment, harm locals' health, and make it more difficult to achieve carbon neutrality, all of which run counter to the government's stated environmental objectives. From an economic and market standpoint, shipping corporations feel there are few ports with the ability to supply shore power, whereas ports think there are not many ships with the capability to use shore power. Nobody wants to take the initiative and make themselves passive. Now is the time for the government to take a two-pronged strategy and develop policies that would encourage the implementation of shore power projects through incentives and sanctions.

The government subsidizes port renovation and applies carbon emission controls to increase port operating costs. The government encourages the development of the energy structure by funding ship retrofits while imposing environmental protection tariffs on pollutants released through the use of fuel oil. By giving priority to berthing for ships using shore power, ports can entice ship retrofits. Ships can decide whether to employ shore power depending on their financial circumstances.

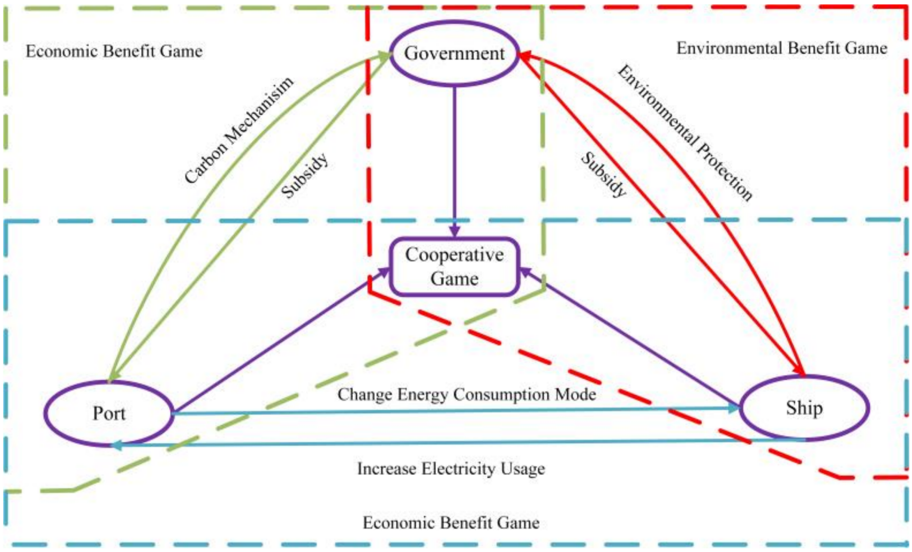

Figure 1. Multiagent game of oil-to-electricity conversion.

Consequently, the three parties' game is impacted by the subsidy rate, carbon mechanism, environmental protection tax, and shore electricity price. The ideal shore power pricing can be attained in the endless game, allowing the electric energy replacement effort to continue.

This article proposes a simple method to calculate the carbon emissions of ports, which only considers the carbon emissions of ships. Other equipment will not be considered, such as harbor railway, quayside container crane, locomotive, and other special machinery. We calculate the carbon emissions of ships using fuel oil and shore power and add the carbon emissions to the economic value, including the port cost. Then, the tripartite economic game models under the two carbon mechanisms are established, respectively, and the impact of the power supply service price, the carbon price, and the proportion of the time using shore power to the docking time on the social welfare, government benefits, port benefits, and ship benefits is discussed.

2.2. Assumptions

To simplify the problem and facilitate modeling and subsequent analysis and discussion, the following assumptions are proposed for the research content:

- The government stipulates carbon emission caps or implements carbon tax policies for ports;
- The created carbon emissions belong to the port once the ship has berthed there.

2.3. Methodology

In order to address climate change, the Ministry of Ecology and Environment of China has formulated "Implementation Plan for Setting and Allocating the Total Amount of Carbon Emission Trading Quotas for 2019–2020 (Power Generation Sector)", which includes enterprises or other economic organizations that emit 26,000 ton of carbon dioxide equivalent or more in any one year from 2013 to 2019. As carbon emissions trading management has only just started, the central government is currently only regulating the power sector. However, in places such as Guangdong Province and Shanghai, it has already started to cover industries such as steel, chemicals, cement, paper, and aviation. The allocation methods are mainly the historical intensity method and the historical emissions method. The former is applicable to industrial enterprises with a high correlation between product output and carbon emissions, and well measured. The latter is suitable for industrial enterprises where the boundary has changed significantly in recent years and it is difficult to apply the industry baseline method or the historical intensity method.

In the historical intensity method, the annual base quota for enterprises is equal to the historical intensity base multiplied by the annual business volume. The historical intensity base is the weighted average of the enterprise's annual business volume of carbon emissions in the previous three years. The annual business volume is the business volume data of the enterprise for the current year verified by a third party verification agency and validated and confirmed by the relevant departments. In the historical emissions approach, an enterprise's annual base allowance is equal to the historical emissions base. In this article, port companies use the historical intensity method and carbon emissions from ports only consider carbon emissions from ships, not from other equipment such as shoreside cranes and locomotives. Thus, carbon emissions are only relevant to the activities of the ship, and the oil or electricity consumed per unit of power has a relevant carbon emission factor to calculate carbon emissions.

2.4. Parameter Descriptions

The following is a description of the parameters that appear in the mathematical model of the three-way game.

$$\begin{cases} P^{k,i} = W_{sp}^{k,i} / T_{sp}^{k,i} \\ W_{sp}^{k} = \sum_{i=1}^{N_i} W_{sp}^{k,i} \\ W_{oil}^{k} = \sum_{i=1}^{N_i} P^{k,i}\left(T^{k,i} - T_{sp}^{k,i}\right) \\ W^{k} = W_{sp}^{k} + W_{oil}^{k} \end{cases} \tag{1}$$

where k denotes the year; i denotes the type of ships; $P^{k,i}$ is the power of the ship's auxiliary engine, kWh; W_{sp}^{k} is the power consumed by the ship using shore power, kWh; W_{oil}^{k} is the power consumed by the ship using fuel oil, kWh; W^{k} is the total power consumption of the ship, kW h; $T^{k,i}$ is the berthing time of the ship, h; $T_{sp}^{k,i}$ is the time when the ship uses shore power, h.

$$C_{dj}^{k} = C_{grid}^{k} + C_{serve}^{k} \tag{2}$$

$$\begin{cases} C_{e}^{k} = W_{sp}^{k} C_{grid}^{k} \\ C_{sp}^{k} = W_{sp}^{k} C_{dj}^{k} \\ T_{e}^{k} = C_{e}^{k} / (1 + 16\%) \times 16\% \\ T_{s}^{k} = W_{sp}^{k} C_{serve}^{k} / (1 + 6\%) \times 6\% \end{cases} \tag{3}$$

where C_{grid}^{k} is the electricity basic price, CMY/kWh; C_{serve}^{k} is the electricity service price, CMY/kWh; C_{dj}^{k} is the electricity actual price, CMY/kWh; C_{e}^{k} is the cost of purchasing electricity for the port, CMY; C_{sp}^{k} is the ship paying the port for electricity, CMY; T_{e}^{k} is to pay value-added tax to the government as the power grid provides electricity to the port, CMY; T_{s}^{k} is the port that makes a profit from providing shore power service to the ship and pays value-added tax to the government, CMY.

$$\begin{cases} C_{oil,sp}^{k} = 10^{-6} W_{sp}^{k} E_1 C_{per-oil} \\ C_{oil,oil}^{k} = 10^{-6} W_{oil}^{k} E_1 C_{per-oil} \end{cases} \tag{4}$$

where $C_{oil,sp}^{k}$ represents the fuel cost savings by the ship using shore power, CMY; $C_{oil,oil}^{k}$ represents the cost of fuel oil used by the ship, CMY; E_1 is the fuel consumption per unit of electricity emitted by the auxiliary engine, g/kWh; $C_{per-oil}$ is the price of marine fuel oil, CMY/Mt.

$$\begin{cases} T_{ep,sp}^{k} = 10^{-3} C_{dl} W_{sp}^{k} \sum_{n=1}^{N_n} F_n / E_{dl}^{n} \\ T_{ep,oil}^{k} = 10^{-3} C_{dl} W_{oil}^{k} \sum_{n=1}^{N_n} F_n / E_{dl}^{n} \end{cases} \quad (5)$$

where n denotes the type of pollutant; $T_{ep,sp}^{k}$ is the environmental protection tax saved by ships using shore power, CMY; $T_{ep,oil}^{k}$ is the environmental protection tax paid by ships using fuel oil, CMY; C_{dl} is the pollution factor pollutant discharge fee standard per unit of pollution equivalent, CMY/equivalent; F_n is the emission factor of pollutants discharged from the fuel oil of the ship's auxiliary engine, g/kWh; E_{dl}^{n} is the pollution equivalent value of pollutants, kg.

$$\begin{cases} V_{sp}^{k} = 10^{-6} W_{sp}^{k} F_e \\ V_{oil}^{k} = 10^{-6} W_{oil}^{k} F_c \\ V_{actual}^{k} = V_{sp}^{k} + V_{oil}^{k} \end{cases} \quad (6)$$

$$\begin{cases} F_{cef}^{k} = 10^{6} V_{actual}^{k} / W^{k} \\ F_{wef}^{k} = 10^{6} \frac{\sum\left(V_{actual}^{k-3} + V_{actual}^{k-2} + V_{actual}^{k-1}\right)}{\sum\left(W^{k-3} + W^{k-2} + W^{k-1}\right)} \end{cases} \quad (7)$$

where V_{sp}^{k} and V_{oil}^{k} are the CO_2 emissions of the ship using shore power and fuel oil, respectively, Mt; V_{actual}^{k} is the total CO_2 emissions of the ship, Mt; F_e is the annual average power supply emission factor of the regional power grid, g/kWh; F_c is the emission factor of carbon dioxide pollutants emitted by marine auxiliary engine fuel oil, g/kWh; F_{cef}^{k} is the comprehensive CO_2 emission factor of the ship, g/kWh; F_{wef}^{k} is the ship's weighted CO_2 emission factor, g/kWh. Equation (6) gives the calculation of the carbon emissions from the use of shore power and the use of oil, respectively, as well as the total emissions for the year. In Equation (7), the ship CO_2 weighted emission factor is taken as the weighted average of the carbon emissions per unit of business of the port in the previous three years, which is used as the base of the historical carbon emission intensity.

$$\begin{cases} V_{cap}^{k} = 10^{-6} \eta F_{wef}^{k} W^{k} \\ T_{c1}^{k} = \left(V_{actual}^{k} - V_{cap}^{k}\right) \times P_{c1}^{k} \end{cases} \quad (8)$$

where V_{quato}^{k} is the port's carbon emission cap, Mt; η is the annual decline coefficient, taking 1; T_{c1}^{k} is the total amount of carbon trading, CMY; P_{c1}^{k} is the carbon price in the carbon trading market, CMY/Mt CO_2. Since only the power sector is currently subject to government regulation and other sectors are not yet subject to excessive restrictions, the annual decline coefficient in Equation (8) is set to 1. This gives the port room to strengthen its efforts to reduce carbon emissions. Carbon emission allowances for the year were calculated, as well as the fees paid in excess of the allowances.

$$T_{c2}^{k} = V_{actual}^{k} \times P_{c2}^{k} \quad (9)$$

where T_{c2}^{k} is the carbon emission tax paid by the port, CMY; P_{c2}^{k} is the carbon tax price, CMY/Mt CO_2.

$$T_{u}^{k} = W_{sp}^{k} / S\omega \cos\varphi \quad (10)$$

where T_{u}^{k} is the annual utilization hours, h; S is the total installed capacity of the shore power system, kVA; ω means that there is a certain margin between the actual use of the shore power capacity of the terminal and the planned construction capacity of shore power; $\cos\varphi$ is the comprehensive power factor of the shore power frequency conversion equipment and the ship's load. We experimentally set $\omega = 0.8$ and $\cos\varphi = 0.7$. ω is needed to make sure that the shore power equipment is working properly under the load. Part of the shore power equipment must be suspended during equipment repairs and maintenance in order to prolong the equipment's useful life. $\cos\varphi$ is related to the nature of the load: different devices have different power factors, so, here, the integrated power is used instead. When W_{sp}^k and S are fixed, obviously, the larger ω and $\cos\varphi$, the smaller T_u^k.

3. Game Research under Two Carbon Mechanism

3.1. Game Research on the Use of Shore Power under Cap and Trade

Figure 2 explains the three-way game model in the case of cap and trade. The government defines carbon emission rights as a commodity and establishes carbon emission caps for ports. By incorporating the value of carbon emissions into port costs, ports can directly buy or sell allowances in the carbon trading market. Ships can voluntarily choose to use shore electricity while they are docked in port and the amount of time they utilize it has been rising every year.

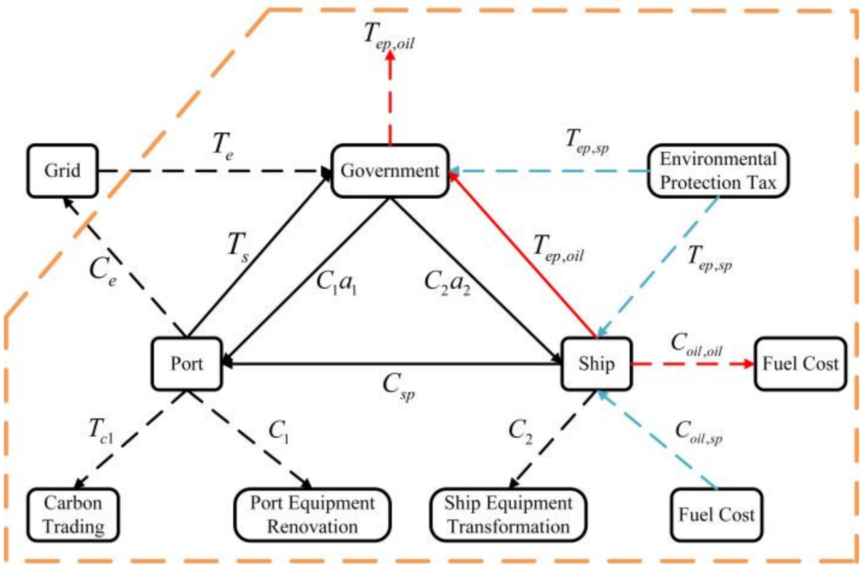

Figure 2. Tripartite benefit analysis under cap and trade.

1. Government Benefit Analysis Model

$$\begin{cases} B_g = T_e + T_s + T_{ep,sp} + T_{ep,oil} \\ C_g = C_1\alpha_1 + C_2\alpha_2 + T_{ep,oil} \\ F_g = B_g - C_g \end{cases} \tag{11}$$

where B_g is the government income; C_g is the government cost; F_g is the government profit; α_1 and α_2 are the subsidy rates for shore power equipment transformation given by the government to the port and the ship, respectively; C_1 and C_2 are the transformation costs of the port and the ship, respectively, CMY.

2. Port Benefit Analysis Model

$$\begin{cases} B_p = C_{sp} + C_1\alpha_1 \\ C_p = C_1 + C_e + T_s + T_{c1} \\ F_p = B_p - C_p \end{cases} \tag{12}$$

where B_p is the port income; C_p is the port cost; F_p is the port profit.

3. Ship Benefit Analysis Model

$$\begin{cases} B_s = C_2\alpha_2 + C_{oil,sp} + T_{ep,sp} \\ C_s = C_{sp} + C_2 + C_{oil,oil} + T_{ep,oil} \\ F_s = B_s - C_s \end{cases} \tag{13}$$

where B_s is the ship income; C_s is the ship cost; F_s is the ship profit.

$$SW_1 = F_p + F_s + T_e + T_s - T_{c1} \tag{14}$$

where SW_1 refers to social welfare, including consumer surplus, producer surplus, government tax, and environmental benefits [31]. $T_{ep,sp}$ represents the environmental benefit, which not only reduces the environmental protection fee levied on the ship but also is included in the government income. Note that social welfare is only counted once and does not accumulate repeatedly.

The use of shore power is abandoned after the ship converts to shore power owing to the high price. In the worst case, all ships consume fuel for power supply. In this way:

$$\begin{cases} B_{s,oil} = C_2\alpha_2 \\ C_{s,oil} = C_{oil,oil} + C_{oil,sp} + T_{sp,oil} + T_{ep,sp} + C_2 \\ F_{s,oil} = B_{s,oil} - C_{s,oil} \end{cases} \tag{15}$$

where $B_{s,oil}$ is the ship income; $C_{s,oil}$ is the ship cost; $F_{s,oil}$ is the ship profit.

When some ships use shore power, the benefits of the entire ship are improved:

$$F_{s,save} = F_s - F_{s,oil} \tag{16}$$

When the ships use all fuel oil, the costs come from the fuel costs and the environmental protection taxes paid. The income comes from freight and is unincluded in the scope of the three-party game, so the ship's benefit is negative, which is similar to social welfare.

3.2. Game Researches on the Use of Shore Power under the Carbon Tax Policy

Figure 3 illustrates the three-way game model in the case of carbon tax policy. The government sets the carbon tax rate, and ports must offer the government a carbon tax for every metric ton of carbon dioxide they emit.

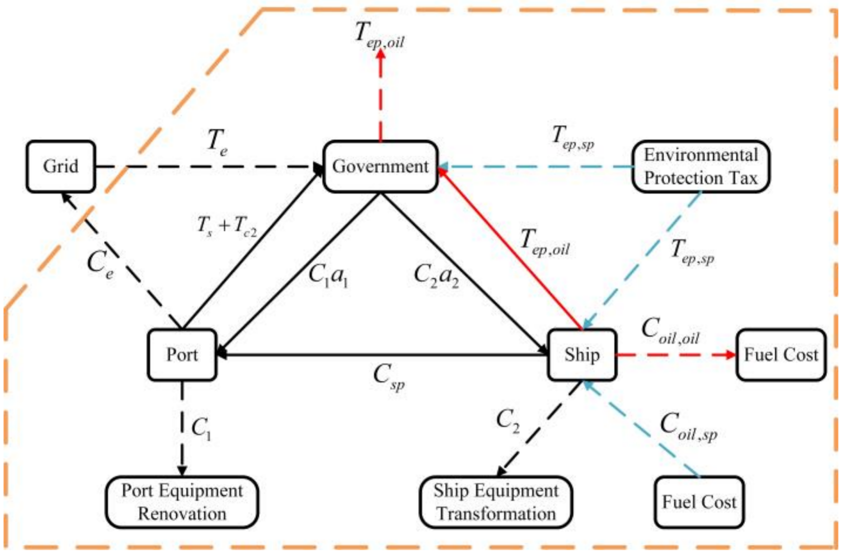

Figure 3. Tripartite benefit analysis under carbon tax policy.

1. Government Benefit Analysis Model

$$\begin{cases} B_g = T_e + T_s + T_{c2} + T_{ep,sp} + T_{ep,oil} \\ C_g = C_1\alpha_1 + C_2\alpha_2 + T_{ep,oil} \\ F_g = B_g - C_g \end{cases} \tag{17}$$

where B_g is the government income; C_g is the government cost; F_g is the government profit.

2. Port Benefit Analysis Model

$$\begin{cases} B_p = C_{sp} + C_1\alpha_1 \\ C_p = C_1 + C_e + T_s + T_{c2} \\ F_p = B_p - C_p \end{cases} \tag{18}$$

where B_p is the port income; C_p is the port cost; F_p is the port profit.

3. Ship Benefit Analysis Model

$$\begin{cases} B_s = C_2\alpha_2 + C_{oil,sp} + T_{ep,sp} \\ C_s = C_{sp} + C_2 + C_{oil,oil} + T_{ep,oil} \\ F_s = B_s - C_s \end{cases} \tag{19}$$

where B_s is the ship income; C_s is the ship cost; F_s is the ship profit.

Social welfare is given by:

$$SW_2 = F_p + F_s + T_e + T_s \tag{20}$$

If all types of ships are powered by fuel oil, the benefit analysis of the ship is as follows:

$$\begin{cases} B_{s,oil} = C_2\alpha_2 \\ C_{s,oil} = C_{oil,oil} + C_{oil,sp} + T_{ep,oil} + T_{ep,sp} + C_2 \\ F_{s,oil} = B_{s,oil} - C_{s,oil} \end{cases} \tag{21}$$

where $B_{s,oil}$ is the ship income; $C_{s,oil}$ is the ship cost; $F_{s,oil}$ is the ship profit.

Some ships are converted from oil to electricity, and the overall benefit of the ship is improved:

$$F_{s,save} = F_s - F_{s,oil} \tag{22}$$

4. Data Selection

4.1. Government Data Acquisition

According to the "Interim Measures for the Management of Subsidy Funds for Ports, Ship Shore Power Facilities and Marine Low Sulfur Oil Subsidy Funds in Shenzhen", the subsidy will be provided for the reconstruction of port shore power facilities, which will not exceed 30% of the project construction costs [32].

4.2. Port Data Acquisition

According to the survey, a port has built 14 sets of shore power systems, covering a total of 23 berths. The installed capacity of the shore power system has reached 11,600 kVA. Including the equipment purchase fee and construction installation fee, the investment and renovation costs of the power equipment are CMY55,144,134. Taking the service life as 30 years, the interest rate of the annualized cost is 8%, which is equivalent to the annual renovation cost:

$$C_1 = \frac{8\% \times (1+8\%)^{30}}{(1+8\%)^{30} - 1} \times 55,144,134 = 4,898,312 \text{ CMY}$$

4.3. Ship Data Acquisition

The investment and transformation cost of onboard electrical equipment, referring to the report of the European Commission Environment Directorate (ECDGE) [33], converted into unit power is 1530 CMY/kW.

The berthing time of the ship in the port, the length of the use of shore power in a certain year, and the electricity consumed by the use of shore power are shown in Figure 4.

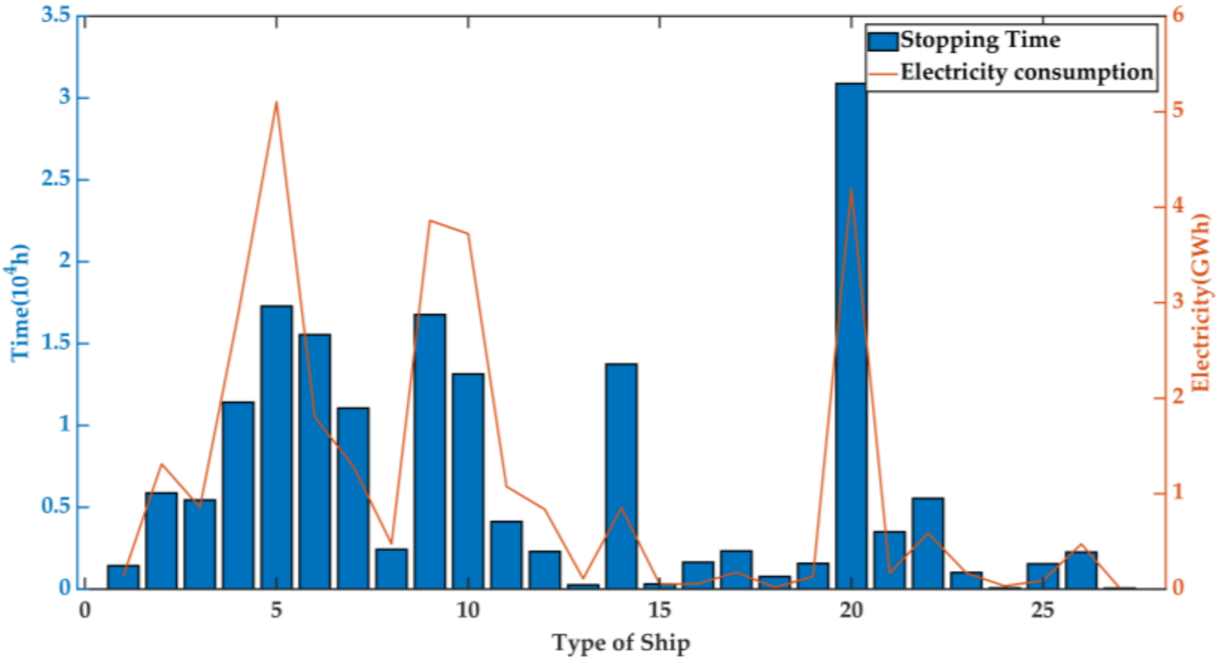

Figure 4. Ship information.

4.4. Electricity Price Acquisition

According to the "Notice on Clarifying the Electricity Price and Service Price of Ship's Shore-based Power Supply Facilities" of the price bureau of Jiangsu province, C^k_{grid} takes the electricity price of large industrial electricity at 0.6601 CMY/kWh. The maximum price of shore power used by ships in Taizhou is 1.20 CMY/kWh [34].

In order to standardize the accounting of carbon dioxide emissions implied by electricity consumption by regions, industries, enterprises, and other units, and to ensure comparability of results, the government organized a study to determine the average carbon dioxide emission factor for regional power grids in China. It refers to the carbon emissions generated by one unit of electricity used in the grid, and is obtained by dividing the total emissions of the entire grid by the total electricity generation. As the port study is in the southern region, the average CO_2 emission factor for the southern regional grid was used. F_e is the annual average power supply emission factor of the regional power grid, taking 527.1 g/kWh.

4.5. Pollutant Data Acquisition

According to the literature [33], E_1 is taken as 213 g/kWh. According to the "2020 Implementation Plan for the Global Sulfur Restriction Order for Marine Fuel Oil" issued by the China Maritime Safety Administration, those entering the country's inland river ships' air pollutant emission control areas should use fuel oil with a sulfur content of no more than 0.10% [35]. $C_{per-oil}$ was taken as 3800 CMY/Mt.

According to the "Decision of the Standing Committee of the Jiangsu Provincial People's Congress on the Applicable Tax Amount of Environmental Protection Tax for Air Pollutants and Water Pollutants", the tax rate in Nanjing is CMY8.4 per pollution equivalent of air pollutants [36].

The annual emission factors and pollution equivalent values of various pollutants caused by marine auxiliary engine fuel are shown in Table 1 [37,38].

Table 1. Annual emission factors and pollution equivalent values of pollutants.

Marine Fuel Emission Pollutants	F_n (g/kWh)	E_{dl}^{n} (kg)
SO_2	0.46	0.95
NO_x	11.80	0.95
VOC	0.53	0.05
CO	1.68	16.7
general dust PM10	0.30	4
CO_2	698	5000

4.6. Carbon Price Data Acquisition

The carbon price data from 2020 to 2050 comes from the "2020 China Carbon Price Survey" [39]. Figure 5 reveals that there has been a steady increase in the carbon price in China since 2020.

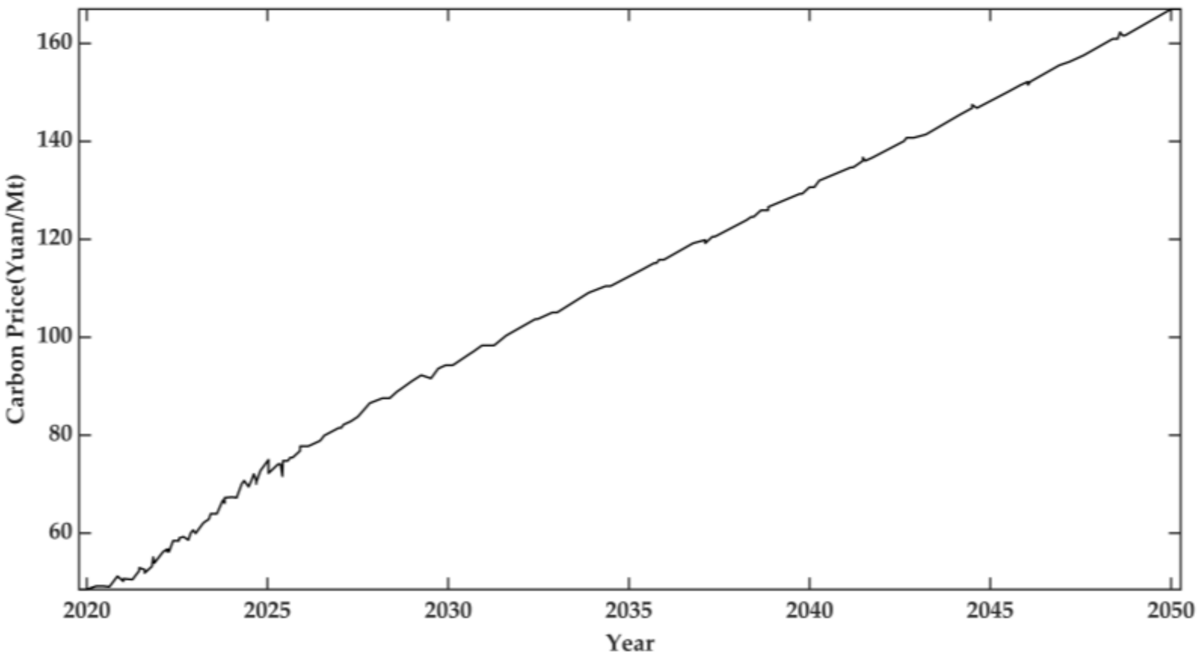

Figure 5. The expected price of the national carbon emissions trading market in 2021–2050.

5. The Impact of Various Factors on the Benefits of Each Party

5.1. Comparison of the Impact of Subsidy Rates

Based on the maximization of social welfare, we explore the impact of subsidy rates under two carbon mechanisms on the optimal price and the benefits to all parties.

Restrictions:

$$\begin{cases} 0 \le a_1 \le 30\% \quad 0 \le a_2 \le 30\% \quad C_{serve} \ge 0 \quad 0 \le C_{dj} \le 1.2 \\ F_g \ge 0 \quad F_p \ge 0 \quad F_{s,save} \ge 0 \end{cases} \tag{23}$$

Objective function:

$$\max.SW \tag{24}$$

Tables 2 and 3 state the impact of the subsidy rate on the economic and environmental benefits of each party in the three-way game model under the two carbon regimes, respectively.

Table 2. Comparison of the impact of subsidy rates on economic benefits to all parties under the two carbon regimes.

Carbon Mechanism	Cap and Trade	Carbon Tax
Subsidy rate a1 (%)	30	30
Subsidy rate a2 (%)	30	30
Electricity service price (CMY/kWh)	0.1151	0.2855
Electricity actual price (CMY/kWh)	0.7752	0.9456
Electricity consumption (GWh)	30.484	30.484
Annual utilization hours (h)	4692.8	4692.8
Social welfare (million CMY)	−104.937	−109.959
Government benefit (million CMY)	7.570	12.647
Port benefit (million CMY)	4.657×10^{-16}	9.313×10^{-16}
Ship benefit (million CMY)	−108.031	−113.228
Savings from "oil-to-electricity" ships (million CMY)	37.917	32.720

Table 3. Comparison of the impact of subsidy rates on environmental benefits to all parties under the two carbon regimes.

Carbon Mechanism	Cap and Trade	Carbon Tax
Carbon cap (Mt)	98,051.842	
Carbon price (CMY/Mt)	50	50
Actual CO_2 emissions (Mt)	95,649.611	95,649.611
Tax involved in carbon mechanism (million CMY)	−0.120	4.782
Environmental tax savings (million CMY)	6.100	6.100
CO_2 reduction (Mt)	5209.746	5209.746
SO_2 reduction (Mt)	14.023	14.023
NO_x reduction (Mt)	359.713	359.713
VOC reduction (Mt)	16.157	16.157
CO reduction (Mt)	51.213	51.213
General dust PM10 reduction (Mt)	9.145	9.145

As can be seen from Figure 6a, whether under the cap-and-trade or the carbon tax policy, social welfare decreases when the electricity service price rises with roughly a linear negative correlation between the two. The cost of power supply services is rising, which does not promote social welfare, and there is clear resistance to the use of shore power. In addition, the lowest value of social welfare under cap and trade is much higher than the maximum value under a carbon tax policy. As a result, cap and trade offers a significant benefit in this case and merits consideration. From Figure 6b–e, we can observe that the subsidy rate a1 affects social welfare, port benefit, and ship benefit to a larger extent than a2 affects all three. The social welfare and ship benefits rise as the subsidy rate a1 rises. The effects of a1 and a2 on government benefits are identical. Government benefits rise with an increase in a2, while they decline with an increase in a1. A comparison of the two results reveals that the cap-and-trade group reported far more social welfare and ship benefits than the other one. On the contrary, the government benefit and port benefit under cap and trade are in every case short of what they are under the other system.

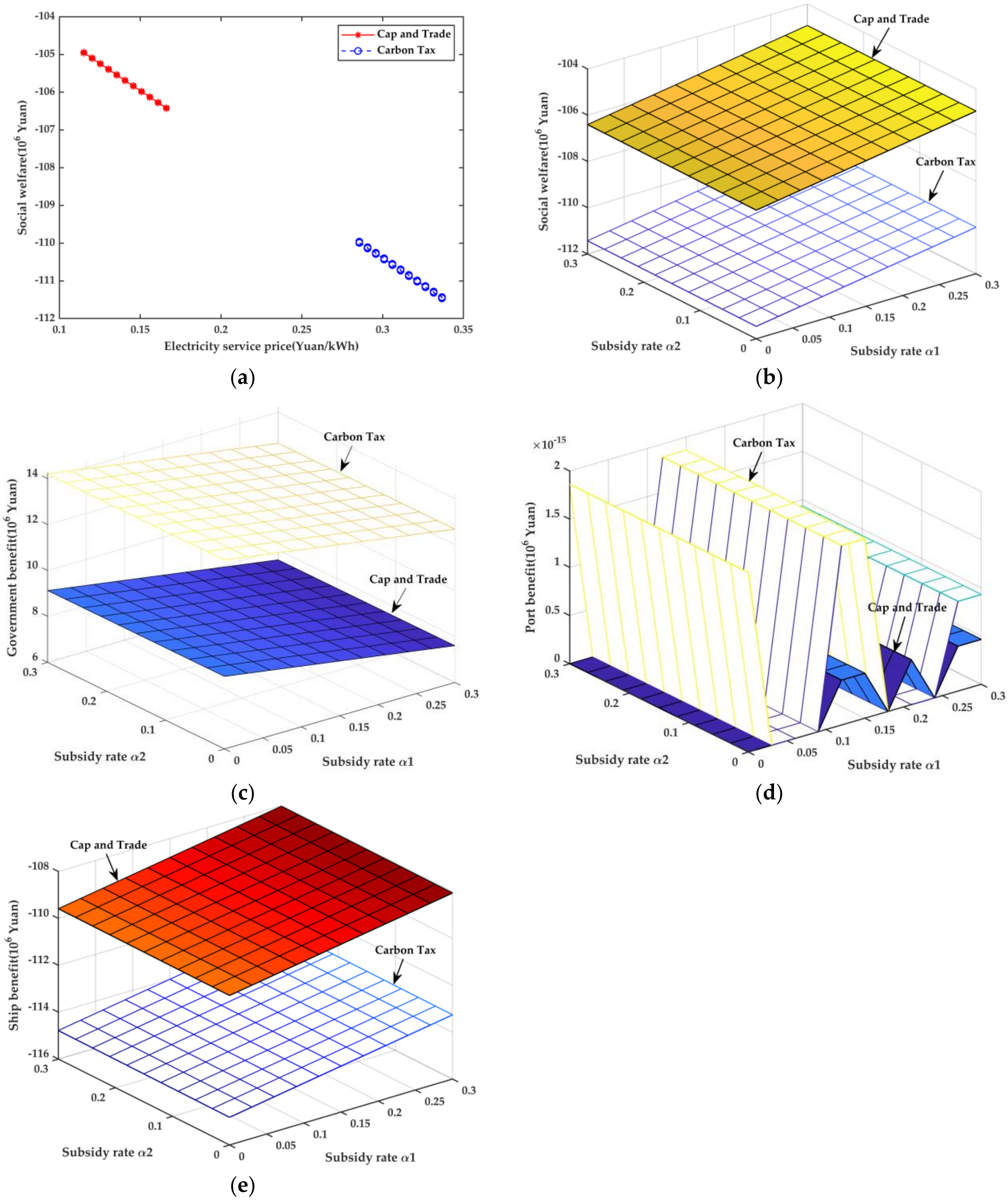

Figure 6. The relationship between subsidies and the benefits to all parties. (**a**) The relationship between electricity service price and social welfare; (**b**) The relationship between subsidy and social welfare; (**c**) The relationship between subsidy and government benefit; (**d**) The relationship between subsidy and port benefit; (**e**) The relationship between subsidy and ship benefit.

5.2. Carbon Price Impact Comparisons

We evaluated how the price of carbon affects the best price and the gains for all parties under two carbon mechanisms based on the maximization of social welfare.

Restrictions:

$$\begin{cases} 20 \le P_c \le 100 \quad C_{serve} \ge 0 \quad 0 \le C_{dj} \le 1.2 \\ F_g \ge 0 \quad F_p \ge 0 \quad F_{s,save} \ge 0 \end{cases} \tag{25}$$

Objective function:

$$\max.SW \tag{26}$$

Tables 4 and 5 indicate the impact of the carbon price on the economic and environmental benefits of each party in the three-way game model under the two carbon regimes, respectively.

Table 4. Comparison of the impact of carbon price on economic benefits to all parties under the two carbon regimes.

Carbon Mechanism	Cap and Trade	Carbon Tax
Subsidy rate a1 (%)	30	30
Subsidy rate a2 (%)	30	30
Electricity service price (CMY/kWh)	0.1109	0.1857
Electricity actual price (CMY/kWh)	0.7710	0.8458
Electricity consumption (GWh)	30.484	30.484
Annual utilization hours (h)	4692.8	4692.8
Social welfare (million CMY)	−104.696	−107.090
Government benefit (million CMY)	7.563	9.605
Port benefit (million CMY)	0	0
Ship benefit (million CMY)	−107.904	−110.186
Savings from "oil-to-electricity" ships (million CMY)	38.045	35.762

Table 5. Comparison of the impact of carbon price on environmental benefits to all parties under the two carbon regimes.

Carbon Mechanism	Cap and Trade	Carbon Tax
Carbon cap (Mt)	98,051.842	
Carbon price (CMY/Mt)	100	20
Actual CO_2 emissions (Mt)	95,649.611	95,649.611
Tax involved in carbon mechanism (million CMY)	−0.240	1.913
Environmental tax savings (million CMY)	6.100	6.100
CO_2 reduction (Mt)	5209.746	5209.746
SO_2 reduction (Mt)	14.023	14.023
NO_x reduction (Mt)	359.713	359.713
VOC reduction (Mt)	16.157	16.157
CO reduction (Mt)	51.213	51.213
General dust PM10 reduction (Mt)	9.145	9.145

Figure 7 compares the outcomes gained from the analysis of the two carbon mechanisms. Under both the cap-and-trade and carbon tax policies, social welfare decreases as electricity service prices rise. The social welfare under cap and trade is always greater than that under the carbon tax policy. Figure 7b–e shows that the price of carbon has a significant impact on social welfare, government benefits, port benefits, and ship benefits under the carbon tax policy. The four are not significantly impacted by the carbon price under cap and trade. According to the cap-and-trade model, while government benefits decline as the price of carbon rises, social welfare and ship benefits increase. The carbon tax policy states that when carbon prices rise, the government gains more advantages whereas social welfare and ship benefits decline. Social welfare and ship benefits under cap and trade tend to be invariably greater than those under the carbon tax approach. In comparison to a carbon tax, the government's benefit under cap and trade is always less. The port efficiency fluctuates positively around 0.

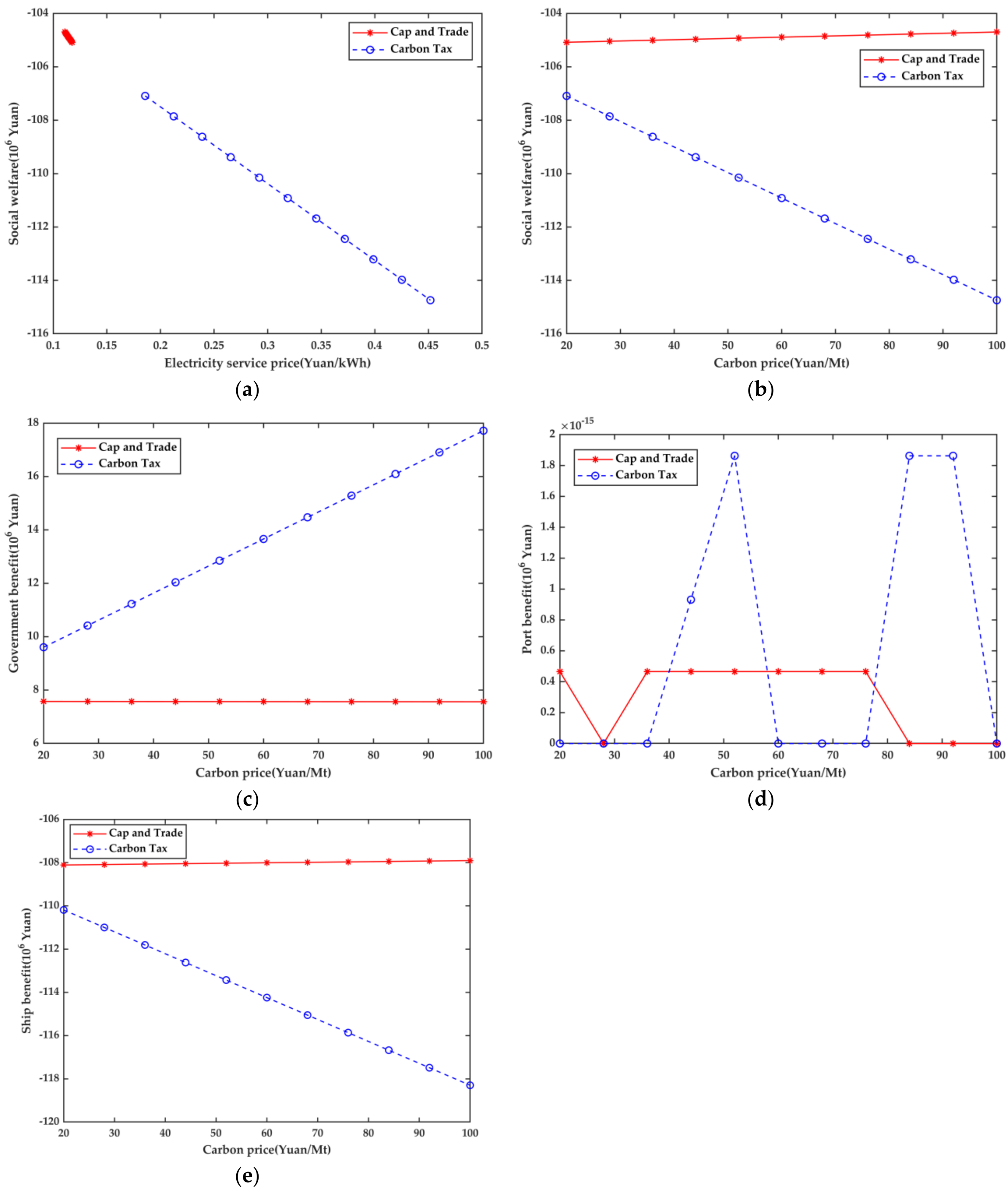

Figure 7. The relationship between carbon price and the benefits to all parties. (**a**) The relationship between electricity service price and social welfare; (**b**) The relationship between carbon price and social welfare; (**c**) The relationship between carbon price and government benefit; (**d**) The relationship between carbon price and port benefit; (**e**) The relationship between carbon price and ship benefit.

5.3. Comparison of Time-Proportional Effects of Using Shore Power

This study investigates the impact of the ratio of time spent using shore power to total docking time on the best pricing and the gains for all parties under two carbon mechanisms, based on the maximization of total social welfare.

$$T_u^k = \lambda \sum_{i=1}^{N_i} T^{k,i} P^{k,i} / S\omega \cos\varphi \tag{27}$$

where λ is the ratio of using shore power to the berthing time. As the total port call time is constant, T_u^k and λ are proportional. T_u^k decreases, so λ decreases, which affects all aspects of electricity prices, social welfare, government benefits, port benefits, ship benefits, etc.

Restrictions:

$$C_{serve} \geq 0 \quad 0 \leq C_{dj} \leq 1.2 \quad T_u \leq 8760 \tag{28}$$

Objective function:

$$\max.SW \tag{29}$$

Tables 6 and 7 explicate the impact of the time-proportional on the economic and environmental benefits of each party in the three-way game model under the two carbon regimes, respectively.

Table 6. Comparison of the impact of time-proportional on economic benefits to all parties under the two carbon regimes.

Carbon Mechanism	Cap and Trade	Carbon Tax
Subsidy rate a1 (%)	30	30
Subsidy rate a2 (%)	30	30
Electricity service price (CMY/kWh)	0.5399	0.5399
Electricity actual price (CMY/kWh)	1.2	1.2
Proportion of time using shore power (%)	39	39
Electricity consumption (GWh)	56.354	56.354
Annual utilization hours (h)	8675.2	8675.2
Social welfare (million CMY)	−66.986	−72.230
Government benefit (million CMY)	16.625	21.187
Port benefit (million CMY)	25.616	20.713
Ship benefit (million CMY)	−99.796	−99.796
Savings from "oil-to-electricity" ships (million CMY)	46.153	46.153

Table 7. Comparison of the impact of time-proportional on environmental benefits to all parties under the two carbon regimes.

Carbon Mechanism	Cap and Trade	Carbon Tax
Carbon cap (Mt)	98,051.842	
Carbon price (CMY/Mt)	50	50
Actual CO_2 emissions (Mt)	91,228.445	91,228.445
Tax involved in carbon mechanism (million CMY)	−0.341	4.561
Environmental tax savings (million CMY)	11.276	11.276
CO_2 reduction (Mt)	9630.913	9630.913
SO_2 reduction (Mt)	25.923	25.923
NO_x reduction (Mt)	664.978	664.978
VOC reduction (Mt)	29.868	29.868
CO reduction (Mt)	94.675	94.675
General dust PM10 reduction (Mt)	16.906	16.906

What stands out in Figure 8a is the price of electricity supply service changes regularly between 0 and 0.5399 CMY/kWh, and social welfare is also changing. The service price must be 0.5399/kWh under cap and trade in order to reach its maximum value, and it must be 0 under the carbon tax policy in order to reach its minimum value. In Figure 8b–d, the similarity between the two carbon mechanisms is highlighted above. The overall level of social welfare rises as the ratio of time spent utilizing shore power to docking time grows. Under the two carbon mechanisms, the change curves for overall social welfare, government benefits, and port benefits are comparable and can be attained by moving up and down. The curve of ship benefit with the time proportion of using shore power is exactly the same in Figure 8e. With the share of time spent utilizing shore power increasing, the overall level of social welfare rises monotonically. However, government benefits, port benefits, and ship benefits show an upward trend with the increase in the proportion of time when shore power is used.

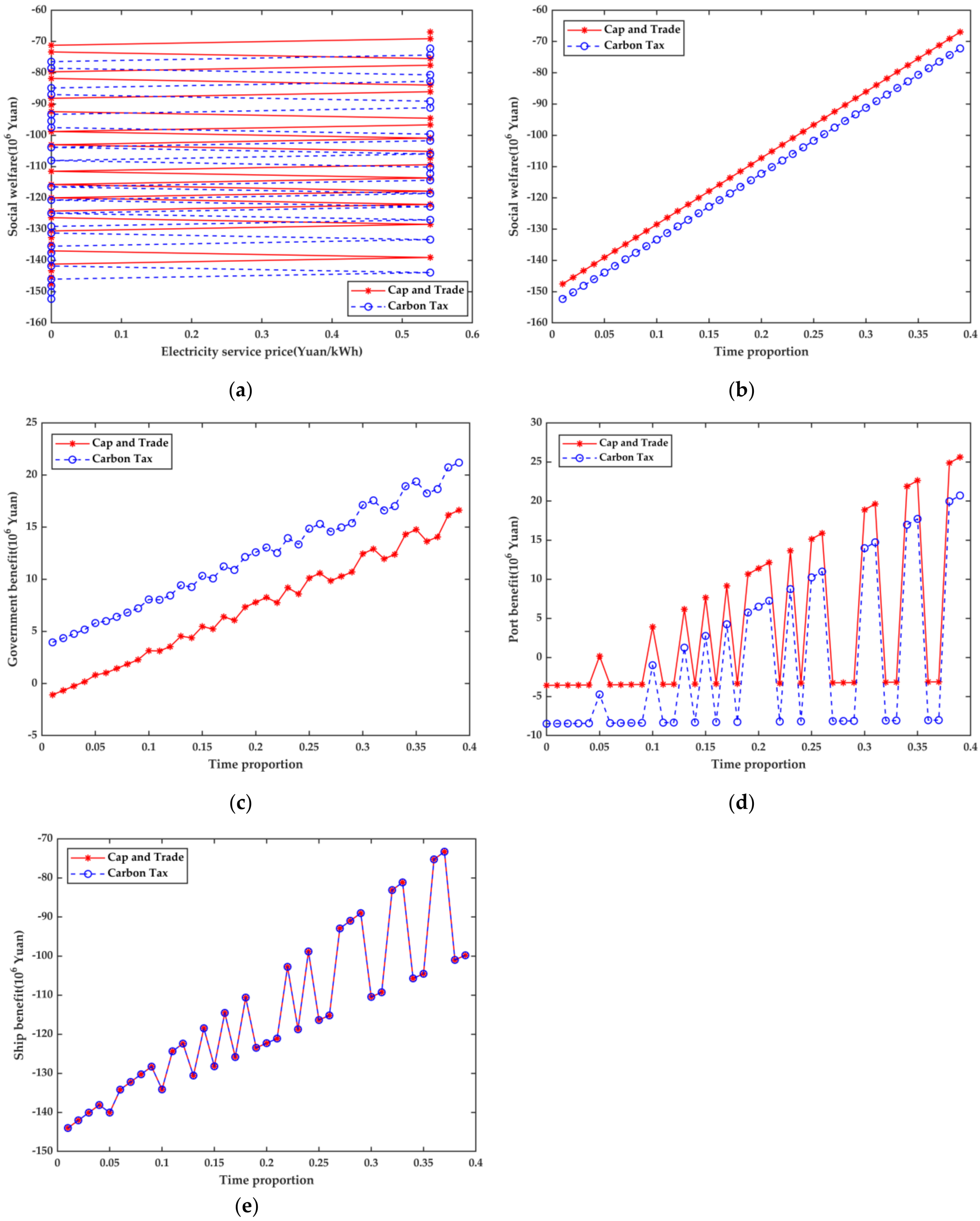

Figure 8. The relationship between time proportion and the benefits to all parties. (**a**) The relationship between electricity service price and social welfare; (**b**) The relationship between time proportion and social welfare; (**c**) The relationship between time proportion and government benefit; (**d**) The relationship between time proportion and port benefit; (**e**) The relationship between time proportion and ship benefit.

6. Conclusions

The two systems of cap and trade and carbon tax are clear and easy to understand, but too many similar parameters appear in the modeling process, leading to easy confusion. In both cap and trade and carbon tax, the specific components of tripartite benefits and social welfare are different and are simply represented by the same parameters, and the specific values change as the electricity service price, carbon tax, and the ratio of using shore power to the berthing time change. Also note that the government is happy to see and promote the use of shore power, which is in line with the plan to reduce carbon emissions; the port is to take the responsibility of a state-owned enterprise, respond to the national policy, take responsibility for emission reduction and establish a good image among the public. Ships have the least public pressure and social responsibility, and they are oriented by economic interests, so they are more unstable, and they need government guidance and support because they have to face technical and economic difficulties in the "oil-to-electricity" conversion. In the model, we should focus on understanding the cost saving of some ships after "oil-to-electricity" conversion, which is the key to decide whether ships should insist on using shore power. There is a difference between the CO_2 emitted from using oil to meet the power and the CO_2 emitted from switching to shore power to replace this power, and the focus is on calculating the difference and the accompanying economic and environmental benefits.

Depending on the port's yearly business volume and historical carbon emission intensity base, the government calculates the annual carbon cap for the port. The comprehensive CO_2 emission factor of ships in the first three years is greater than the current year's CO_2 emission factor. Therefore, the carbon cap is frequently higher than the actual CO_2 emission, according to calculations of the port's real energy usage. Currently, compared to other businesses, the government's criteria for reducing carbon emissions in the maritime sector are not stringent enough.

In summary, these results indicate that the annual hours of shore power facility use, the amount of environmental protection tax saved by utilizing shore power, and the reduction in pollutants and carbon dioxide are all equivalent as long as the ships' energy consumption is constant. The social welfare, governmental benefits, port benefits, and ship benefits appear to vary depending on the subsidy rate, carbon price, and percentage of time using shore power.

It is reasonable for the port to set the shore electricity price within the range of 0.6601 to 1.2 CMY/kWh, taking into consideration both its own transformation costs and government subsidies. As long as ships use electricity instead of fuel, the economic benefits will be significantly improved, no matter what changes in various carbon mechanisms and influencing factors. The primary source of improvement may partly be related to reduced fuel costs. The government's benefits are always greater than zero, mostly due to the environmental benefits of decreasing pollutant emissions. Low economic advantages are expected for the port, as a result of high costs of self-renovation and government limits on the actual electricity price.

The major limitation of this study is that ships are assumed to be equivalent to a virtual ship although they have distinct types and numbers when in berth. It is a macro analysis for multiagent games; hence, it cannot accurately reflect the benefit to an individual ship. The three-party game is dynamic and played repeatedly, and ships are allowed to choose whether to utilize shore power or not, which makes it challenging to calculate the best electricity price. By examining the status of the tripartite game in electricity substitution, this study offers a particular reference value for the cycle planning and benefit distribution of electric energy replacement projects in the future.

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Article

Combustion, Ecological, and Energetic Indicators for Mixtures of Hydrotreated Vegetable Oil (HVO) with Duck Fat Applied as Fuel in a Compression Ignition Engine

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Abstract: The aim of the present study was to investigate the effects of the application of hydrotreated vegetable oil (HVO) mixed with pure duck fat (F100) as fuel, replacing the conventional fossil diesel fuel (D100). The tests were performed using a four-stroke direct injection CI engine diesel engine. Six fuel samples were used: D100, HVO100, F100, as well as three HVO–fat mixtures F25, F50, and F75. To further study the main characteristics of fuel combustion, the AVL BOOST software (Burn program) was applied. The results of experimental studies showed that with the addition of pure fat to HVO, the ignition delay phase increased with an increase in the amount of heat released during the premix combustion phase and the pressure and temperature rise in the cylinder increased; however, the mentioned parameters were not higher as compared to diesel fuel. It was found that as the concentration of fat in the HVO–fat mixtures increases, the viscosity and density increases, while LHV was decreased, which thereby increases brake specific fuel consumption and slightly decreases brake thermal efficiency in comparison to diesel fuel. A decrease of CO_2, HC, NO_x emissions, and smoke was established for all HVO–fat mixtures as compared to diesel fuel at all loads; however; under low loads, CO emissions increased.

Keywords: combustion; fuel; emissions; engine

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1. Introduction

The lack of components and raw materials mined in Ukraine and Russia, as well as international sanctions, are only part of the war-related crises that the automotive industry has experienced.

The rapid decline in hydrocarbon reserves and the constant rise in prices for them require large-scale development of renewable energy sources [1–3]. Moreover, an important reason stimulating the transition to alternative energy sources are the problems of global climate change, which will reduce the impact on the environment of harmful factors, improve the ecology of our planet, as well as implement the recommendations written in the "Paris Convention on Climate Change", which entered into action on 4 November 2016 [4,5].

The current situation calls for regulation of the biofuels sector in 2023 with regard to the possibilities and obligations for the use of biocomponents in fuels. The aim is to contain further increases in fuel prices, to stabilize the situation involving the national fuel and biofuel markets, and to increase the state's fuel safety.

The EU biofuel policy aims to promote and encourage the development of biofuels, such as biodiesel, bioethanol, and biomass [6,7]. The Energy Union strategy, entitled "Clean energy for all Europeans" published in 2016, highlighted the further measures to reduce CO_2 emissions by up to 40% by 2030 and have net zero by 2050 [8,9].

As a result of environmental policies, many automotive alliances and partnerships have emerged to work together on large-scale biofuel projects. For example, FCA teamed up with Tesla and Honda, Mazda with Toyota, and Ford with Volvo and Polestar [10]. Since 1990 emissions of CO_2 in Europe have reduced by about 24% [11].

The European Union is the leader in the use of diesel biocomponents, the region accounts for 41% of the world demand for diesel biocomponents, which is 15.9 million tons, or about 7.4% of the volume of diesel fuel consumption in the EU. The vast majority of biocomponents used in the EU—about 85.5% (13.6 million tons)—are FAME (fatty acid methyl esters), the remaining 14.5% (2.3 million tons) are HVO. Of this volume, 11.6 million tons of FAME are produced directly in the EU countries and 2.7 Mt of HVO [12]. The HVO system enables the industrial application of the hydrogenation of rapeseed oil, used cooking oil (UCO), or a mixture of both. The final product may be used as an additive to diesel or jet fuel.

Experts predict that this figure will be 70% by 2030. Thus, the environmental and economic indicators for numerous countries, for instance Poland, Slovakia, Malta, Bulgaria, and Estonia, will be even more vulnerable to the impact of the transport industry [13].

The recently adopted European Climate Law raises the EU's 2030 vehicle emissions target from 40% to a minimum of 55% and introduces a legislative commitment to carbon neutrality by 2050, which, in turn, should help reduce emissions of CO_2 in the volume of about 420 million tons per year [13].

Today, most experts [14–19] agree that an important factor for the creation and use of innovative fuels for diesel engines is the availability of extensive raw materials for the production of alternative motor fuels. The energy features of the presented sources of raw materials, similar to mineral fuels, make it possible to use the latter as motor fuels [20].

The balance of the combination of rational prices for raw materials and measures to regulate social and environmental risks is of particular importance [21].

Hydrogenated vegetable oil (HVO) was introduced in 2005 when it was derived exclusively from palm oil [22]. Free of aromatics, oxygen, and sulfur, hydrogenated vegetable oil has a high cetane number, resulting in reduced NO_x emissions, improved stability in storage, and low temperature properties, making it suitable for almost all diesel engines [23,24]. The main limiting factor in the industrial producing of biodiesel is the cost of vegetable oil. The purchase of oilseeds, transportation, storage, and extraction of oil are the main items of expenditure related with the production of biodiesel. The production of fuel from plants takes up agricultural land, while more pesticides, herbicides, and fertilizers are used for higher yields, making it impossible to continue growing any other plants suitable for food on this area [25].

At the same time, intensive animal husbandry and subsequent processing of raw meat leads to the accumulation of a significant amount of fat-containing raw materials and waste [17,26–28]. This resource can be used to further solve energy problems for the production of biofuel.

Biodiesel can be exploited as pure (B100) or mixed with diesel fuel at any combination in most diesel engines. Generally, the use of such fuel does not require modification of the vehicle's engine [29–31].

Analysis of recent studies and publications suggests that numerous research on alternative fuels for diesel engines focuses more heavily on blending ratios with diesel [32–35], but there is little research evaluating the use of clean duck fat fuels as oxygenated fuels in combination with HVO.

Thus, in the opinion of the authors of this work, it is also important to study the potential of the presented samples of mixtures for further assessment of the main criteria of fuel quality during operating in a diesel engine.

According to most research [18,32,35–39], when biodiesel is burned, the greenhouse effect does not increase; it decreases the content of hydrocarbons, soot, and carbon monoxide exhaust gases. Biodiesel does not contain carcinogenic substances, such as polycyclic aromatic hydrocarbons and especially benzopyrene, with comparison to fossil fuel [40].

Some of the important indicators of engine efficiency are the parameters of the fuel used, in particular: density and kinematic viscosity [18,41,42]. In this paper, [43] noted that biodiesel extracted from duck fat has favorable properties of density, kinematic viscosity, and also, lower heating value compared to diesel fuel.

Animal fat as a fuel component can be widely used due to its cheapness (because it is obtained as a by-product of meat processing) and availability (every country has a meat processing industry). Pure lard is filtered before use, its preparation is carried out (heating to a uniform consistency and repeated filtering) [44]. When choosing the proportions of fat mixtures with traditional fuels, their physicochemical properties must be taken into account [45]. Depending on the type of fat, it is necessary to select measures to prevent it from solidifying in fuel mixtures (chemical stabilizers are used, additional heating, and constant mixing) [46].

The combustion parameters of chicken fat are different compared to traditional diesel fuel, such as a lower rate of heat release, which is determined by prolonged reactions at low temperatures [47]. To improve them, additional hydrogen can be added to fuel containing chicken fat—a better energetic (increased BTE) and ecological effect (decrease in sharpness, CO, and UHC emissions) is achieved [48].

The peculiarity of the high viscosity of the biodiesels is that it tends to negatively affect the loss of engine power. Due a high viscosity, large droplets and a short jet are formed; therefore, it takes more time for the fuel to evaporate, the ignition delay phase increases, incomplete combustion occurs, carbon deposits form, and fuel consumption increases [49]. Poor sprinkling, in turn, leads to clogging of the nozzle and fuel pump, which directly affect the increase in toxic emissions, such as CO, CO_2, and SO_x [50,51]. Besides, the straight using of pure vegetable oil causes the formation of injector sediments, a result of which gives rise to higher exhaust gases [52].

As known, density is one of the key characteristics of petroleum products for diesel engines. The density is determined by the parameters of the fuel itself. The higher the fractional composition, the more difficult the processes of evaporation and atomization of fuel in the injectors become [53].

Hoekman et al. [54] indicated that due to the oxygen content of biofuels, it has a lower content of energy (MJ/kg) than diesel fuel.

It should be noted that biodiesels have a higher cetane number than diesel fuel, which indicates a good ignition rate of the fuel [26,55].

A large number of studies have been carried out to study the consequence on the performance of a diesel engine of biodiesel based on various animal fats [38,56–58].

Şen et al. [38] used chicken fat for the making of biodiesel. In a pilot study, it was noted that the use of biodiesel blends led to a reduce in emissions CO, CO_2, HC, and smokiness, but slightly increased the torque values and indicators NO_x. Raman et al. [49] also found that CO emissions from biodiesel blends are lower than those of a diesel engine, but CO values are higher at low loads. One of the possible reasons is the presence of a rich fuel mixture at higher loads.

In this research [56], the authors investigated duck fat oil used in a single cylinder Kirloskar TV-1 diesel engine. The results have shown that emissions of CO and HC were increased. Opposite results were for CO_2 and NO_x, which was reduced compared to diesel fuel.

Goga et al. [59] used a fuel mixture in their experiment (10% rice bran oil and 90% diesel) and it was found that hydrocarbon emissions are decreased when biodiesel was used as opposed to diesel fuel, which may indicate a shorter ignition delay phase due to a higher cetane number of the biodiesel mixture. Furthermore, it should be said that a shorter ignition delay phase contributes to a more complete combustion of the fuel; consequently, there is less hydrocarbon emission. Other authors [33] also obtained similar results of a decrease in the emission of HC.

Results obtained from experiment with edible sunflower oil and non-edible Karanj oil indicated longer ignition, which consecutively caused an increase in pressure in a cylinder and higher CO and NO_x emissions, while in contrast, demonstrated lower BSFC in comparison to diesel fuel [52].

Additionally, diesel fuel is composed of alkines, cycloalkine, and aromatic hydrocarbons, which, in turn, also increase the formation of smoke.

In this research [23], the effect of pure chicken fat and various mixtures of fat and diesel in the ratio of 70/30, 50/50, and 30/70 was studied. An increase was noted in emissions of CO and CO_2 for mixtures with pure fat. Reduced emissions of NO_x during low engine loads for mixtures due to larger droplets of fuel, which caused a decrease in temperature, was also observed.

The authors [60] point out that high NO_x emissions from biodiesel mixtures may result from the high oxygen content of biodiesel. Barrios et al. have the same opinion [61].

Several publications [36,62] indicate that NO_x emissions are influenced by fuel density. NO_x emissions are also dependent on engine load and rpm, injection timing, and ignition delay [63,64].

Many studies have found that the use of biofuels in a diesel engine improves environmental performance, but at the same time increases BSFC [33,35,36,49,60,62,65,66].

Emiroğlu et al. [42] studied turkey fat as the main raw material for biodiesel in blends. It was found that the mixtures had at all loads with an engine speed from 1600 rpm to 2400 rpm, higher specific fuel consumption (BSFC) values and, at the same time, lower brake thermal efficiency (BTE) values compared to diesel fuel. Rao et al. [67] have similar conclusions. They pointed out that as the percentage of chicken fat biodiesel increased, exhaust temperatures, CO emissions, and BTE declined, while BSFC and NO_x increased. In [68], biodiesel based on chicken fat (B) was blended with diesel fuel (D) in specific blending percent: B20D80, B30D70, B40D60, and B50D50. It was indicated that the lower the engine power, the higher the fat content in the mixture, which is associated with a low calorific value.

Selvan, V.A.M. has made a major contribution to the development of knowledge about the use of fats for energy purposes [69–73]. His experimental studies have shown that chicken fat and egg shell are suitable as catalysts for the production of biodiesel. In addition, he was able to demonstrate that the physicochemical properties of the biodiesel produced from chicken oil comply with the ASTM D 6751 standard. In his scientific studies, Selvan, V.A.M. has shown that skin fat is an excellent source of energy.

Mikulski et al. [33] conducted experimental work on a four-stroke Common Rail diesel engine investigating pork fat methyl esters. It was noted that increasing the methyl ester in the blend increased the BSFC. This was due to the low calorific value of the tested mixtures, and also indicated a shorter ignition delay phase of the fuel. At the same time, an increase in BTE values was observed with an increase in the amount of biodiesel, on average, by 1.6%, 4.8%, and 7.8% for B25, B50, and B75, respectively. The same results are consistent with the solution indicated by Abed et al. [74] and Jayaprabakar et al. [75]. Consequently, the higher fuel consumption of biodiesel fuel contributes to improved fuel combustion due to oxygen enrichment, which also affects the performance of higher exhaust gas temperatures. Analysis of some publications recommends the use of biodiesel blends containing no more than 20% fuel based on renewable sources to minimize losses in engine performance [16,58].

The European Union's climate policy aims at climate neutrality. One way to achieve this is to reduce emissions of harmful gases (including greenhouse gases) from transport as much as possible. A large proportion of vehicle manufacturers selling their products in Europe have declared that they will not sell combustion vehicles between 2030 and 2040.

Electromobility is being developed and promoted in many countries of the European Union. However, there is no way to remove all of the combustion vehicles (approx. 2.5 to 3 billion). This applies to both passenger and truck transport. In the case of heavy vehicles, the problem is even greater. Currently, diesel tractors are responsible for international traffic. They travel thousands of kilometers to transport between states. In this case, electromobility is not yet equipped for these major challenges. On the one hand, there are vehicles that do not yet have sufficient range, and on the other, there is the infrastructure.

Hydrotreated vegetable oil (HVO) could be a solution. This is fuel derived from waste from the food industry, i.e., in reality from residues of vegetables, fruit, and fat products (even animal origin).

Preliminary studies have shown that its benefits include reduced carbon dioxide emissions (between 50% and 90%, depending on the purity) and the absence of sulfur compounds. A 2011 study by VTT of Finland found that older cars can emit up to 30% less carbon dioxide. HVO100 is a pure hydrogenated vegetable oil without the addition of fossil fuels. HVO can also be mixed with conventional diesel in different proportions, e.g., HVO30, HVO50, etc. For new vehicles, HVO reduces CO_2 emissions by about 90%.

In the case of HVO, emissions cannot be avoided during production. This process still requires oil extraction and processing.

Leading truck manufacturers support the spread of the HVO. Compliance with the standards for its entire fleet has been announced by the DAF and has been declared for several years by Scania, MAN, Volvo, Mercedes, Renault, and Iveco. In particular, owners of Euro 5 and Euro 6 compliant lorries will be able to use the new biodiesel, i.e., practically the entire Polish fleet serving international transport as well as most local vehicles. After verification, the HVO mixtures can also refuel Euro 3 and 4 vehicles.

Volkswagen announced that from July 2021 diesel vehicles can be operated with pure HVO. In addition, the group estimates that the share of this fuel will reach up to 30 percent of the energy mix needed for transportation within a decade.

The reduction of pollutant concentrations during the combustion process and the ability of the HVO to act as a substitute fuel for most compression ignition engines makes it worthwhile to develop. Hydro-refined vegetable oil is not emission-free and consumes a fairly large amount of energy, but it is produced from waste that would have to be disposed of anyway.

The main aim of this research is to evaluate the energy and ecological benefits obtained with blends containing HVO and pure fat, as opposed to diesel fuel.

2. Methods and Materials

The study of engine performance indicators using HVO and fat fuel mixtures was carried out by means of experimental and numerical analysis. In the course of the experimental analysis, energy and ecological indicators were determined and the pressure in the cylinder was measured. Analysis of the combustion process was performed with the help of the BURN subroutine of the AVL BOOST program. Summarizing conclusions are presented based on the indicators of experimental and numerical analysis (Figure 1). The algorithms for controlling combustion engines require a considerable amount of time and cost. Engine manufacturers and research centers are increasingly using advanced tools to simulate engine operation. These tests allow a significant reduction in the analysis time and a reduction in the costs of engine design and development. AVL BOOST is a multi-level computing system with the possibility of real-time operation to simulate variable engine conditions. The calculation program simulates engine operation over time using current and constant zero-dimensional and quasi-dimensional components of the model.

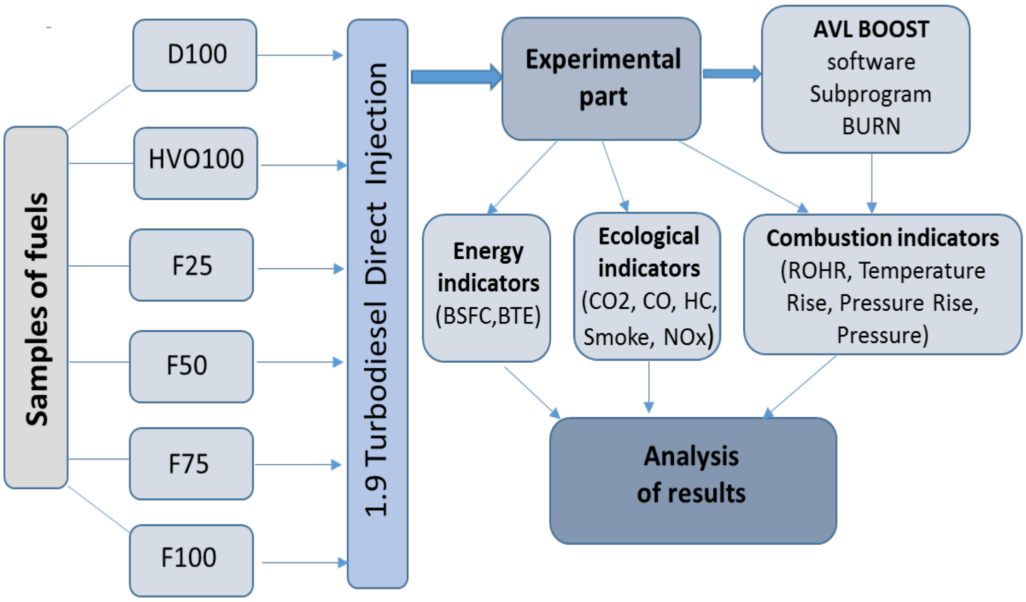

Figure 1. Nomenclature of research.

2.1. Fuel Preparation

The main properties of fuel samples for a CI engine were examined in accordance with fuel standards in the European Union. In the EU, there are two standards for diesel fuel: standard EN 590 for mineral diesel fuel, to which it is allowed to add up to 5% fatty acid methyl esters, and the standard EN 14214—fatty acid methyl esters applying for diesel engines.

For HVO, we applied the recommendation of Neste Renewable Diesel, in that hydrotreated vegetable oil contains paraffinic hydrocarbons, and cannot be equivalent to the requirements of EN 14214, which was proposed solely for fatty acid methyl esters, that is, FAME. Nonetheless, HVO is close to standard EN 590, not including density.

Biodiesel concentrations studied, include mixing, was carried out in the following proportions. Blends of hydrotreated vegetable oil (HVO100) and pure duck fat (F100) mixed in the ratio of F25, F50, and F75 by volume. The comparison of physical and chemical properties of various fuels are given in Table 1.

Table 1. Physicochemical properties of the analyzed fuels.

Fuels	Density (kg/m^3) at 15°	Viscosity (mm^2/s) at 40°	Sulfur Content (mg/kg)	Water Content (mg/kg)	Total Contamination (mg/kg)	Cetane Number	Hydrogen %	Carbon %	Oxygen%	C/H%	LHV (MJ/kg)
Allowed value in accordance with quality standard EN 590											
	820–845	2–4.5	≤10	≤200	≤24	≥51					
D100	823.00	3.5	7.25	85	20	45	0.130	0.870	0.000	6.69	42.70
Allowed value in accordance with quality standard EN 14214											
	860–900	3.5–5	≤10	≤500	≤24	≥51					
F25	800	4.7	4.52	690	43.27	72.04	0.146	0.827	0.027	5.64	42.40
F50	831	9.8	4.87	770	-	67.19	0.141	0.804	0.055	5.70	40.70
F75	867	18.8	5.21	925	-	62.34	0.136	0.782	0.082	5.77	39.00
F100	908	34.8	5.31	1450	-	57.49	0.130	0.760	0.110	5.85	37.30
Allowed value in accordance with the booklet information on Neste Renewable Diesel for HVO											
	770–790	2–4	≤5	≤200	≤10	>70					
HVO100	776.00	2.9	4.16	20	5.52	76.89	0.152	0.848	0.000	5.58	43.70

Physicochemical properties of biodiesel made from animal fats or vegetable oils, in particular, viscosity, density, heat of combustion, cetane number, etc., differ from those for diesel fuel. It can be noted that the fuel mixtures presented are within the normal range. To ensure proper viscosity, duck fat fuel was heated to 40–50 °C.

Thus, the above analysis of the physicochemical properties of hydrotreated vegetable oil and its mixtures with pure duck fat indicates the possibility of using most of them to power diesel engines, despite the weighted fractional composition of fat; hence, with increased viscosity. However, these differences in the properties of pure fat and mixtures based on them from the properties of diesel fuel can lead to a deterioration in the quality of fuel atomization and mixture formation [68]. Therefore, it is preferable to use low fat hydrotreated vegetable oil in diesel engines; the less the viscosity of the fuel, the easier the fuel supply and its atomization (Table 1).

2.2. Test Bench, Measuring Instruments, and Data Processing

Specifications of the engine used in the experiment are given in Table 2. During the experimental part, the engine was taken at fixed speed n = 2000 rpm, the engine brake torque (MB) was presented in 30 Nm, 60 Nm, 90 Nm, and 120 Nm, which meant the brake mean effective pressure (BMEP) was 0.2 MPa, 0.4 MPa, 0.6 MPa and 0.8 MPa.

Table 2. Specifications of the engine used in the experiment.

Specification	Parameter
Engine	1.9 Turbodiesel Direct Injection
Number of cylinders	4
Compression ratio	19.5
Stroke	95.5 mm
Bore	79.5 mm
Maximum power output	66 kW at 4000 rpm
Maximum torque	182 Nm at 2000–2500 rpm

The tests were carried out at the stand used in the direct injection of the CI engine equipped with the electronic control unit. For measuring the composition of exhaust gases CO, HC, NO_x, smoke, and CO_2, the instrument AVL DiCom 4000 was applied, with precision of the result of 0.01% for CO, and for HC and NO_x, respectively, 1 ppm, and smoke 0.01 m^{-1}, and 0.1% for CO_2. The consumption of the tested fuel samples was carried out by weighing them on an electronic balance, CK-5000, with precision of 1.0 g. Therefore, an air meter was used to measure the air flow BOSCH HFM 5, with an accuracy of 2%. Pressure sensor Delta OHM HD 2304.0 measured the pressure of the turbocharger, with an accuracy of 0.0002 MPa. The temperature was measured using a thermoelectric converter, with an accuracy of 1.5 C (Figure 2).

In order to ensure uniformity of results and to avoid random errors, each test point was repeated 5 times. Such repeatability showed that during the test the recording of the results was done only when the smooth operation of the engine was established.

During the experimental tests, the CO concentration was measured, the accuracy of the measurement was 0.01%. At low engine load (BMEP = 0.2 MPa) and the engine running on HVO fuel, the CO concentration was 0.01%, with F100 fuel the CO concentration was close to 0.03%. When the engine was running at a load of BMEP = 0.8 MPa, the CO concentration of all fuels was the same—0.01%. The pollutant concentration was recalculated into a specific emission g/kWh and the obtained results correlate with the experimental data.

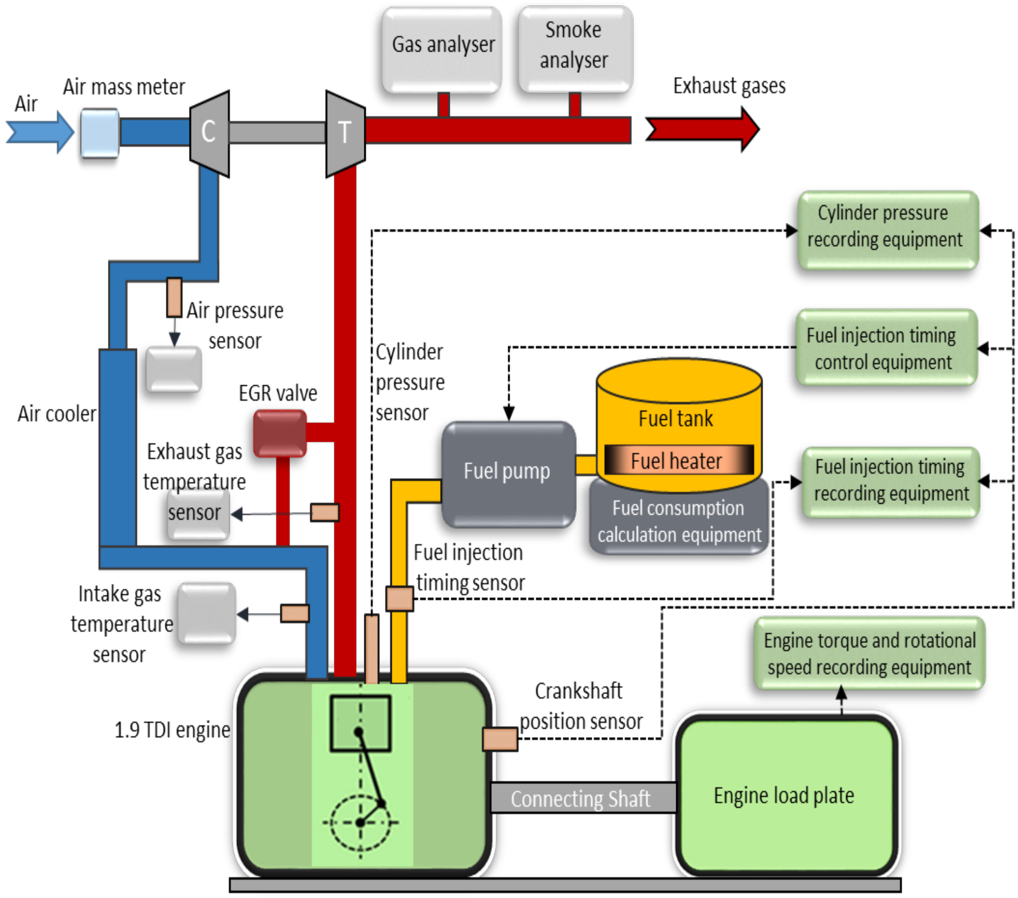

Figure 2. Schematic internal combustion engine testing equipment.

The piston position at the top dead center (TDC) was determined by an optical crankshaft position sensor, A58M-F, with signal repeatability of 0.176 CAD. To convert the signals from the pressure and crankshaft position sensors, the device AVL DiTEST DPM 800 was used. A quartz piezoelectric sensor was used to measure the gas pressure in the cylinder. AVL GH13P had a sensitivity of 15.84 ± 0.09 pC/bar. LabView Real software recorded the engine pressure (100 cycles). Registration of the start of fuel injection was noted by the equipment VAG-COM. The fuel injection timing control equipment controlled the fuel injection process.

During the tests, each point was repeated 5 times after the engine had stabilized. Standard error statistical evaluation was used:

$$u\left(\bar{x}\right) = u(x)/\sqrt{n} \tag{1}$$

where, the number of repetitions, in the case, was equal to 5.

Further, the errors were evaluated according to the sources [76,77] in the calculation and expanded uncertainly $U_{0.99}$.

The error values are shown in Table 3.

Table 3. The error values.

Parameter	Standard Uncertainly u	Expanded Uncertainly $U_{0.99}$
ROHR, J/CAD	0.003657	0.025
Temperature rise K/deg	0.002987	0.017
Pressure rise in cylinder, MPa/deg	0.005987	0.036
Pressure in cylinder, MPa	0.005745	0.034
CO_2, g/kWh	0.000301	0.007
CO, g/kWh	0.000258	0.006
HC, g/kWh	0.006987	0.041
Smoke, m^{-1}	0.000249	0.005
NO_x, g/kWh	0.007459	0.052
BSFC, g/kWh	0.005221	0.032
BTE	0.003698	0.025

2.3. Analysis of Experimental Results with the Use of AVL Boost Software

The fuel combustion processes were further studied by means of the software AVL Boost. AVL Boost is a software that includes of a pre-processing program for the starting data and description of the engine that will be represented as a model. Thereafter, the system applications form the mathematical equations and algorithmic program with a illustrative user interface, and inspect and calculate the processes that will be needed in the analysis and modeling. The software AVL BOOST's subprogram BURN uses the experimental data: cylinder pressure, as well as fuel and air consumption, properties of tested fuel samples, etc. By means of the subprogram BURN, the start of combustion (SOC), combustion duration (CD), and shape parameter (m) was determined. Furthermore, the rate of heat release (ROHR), temperature, and pressure rise in the cylinder were observed.

3. Results and Discussion

3.1. Indicators of Combustion

The combustion process is affected by both the structure and size of fuel droplets, the difference in the molecular structure of fuel hydrocarbons, the types of hydrocarbon compounds, and the types of chemical intermolecular bonds [78]. These characteristics of the fuel supplied for combustion have a significant effect on the qualitative and quantitative characteristics of the combustion process, and on the oxidation reactions of hydrocarbon compounds in the combustion zone [53].

The start of combustion (SOC) and ignition delay (ID) for various fuels at engine load BMEP = 0.8 MPa are shown in Figure 3. From the analysis of the experimental data, it can be found that SOI = 7 CAD bTDC for all fuels. The ignition delay phase for different fuels increases in the following order: HVO100, F25, F50, F75, F100, and D100. The shorter ignition delay phase of biofuel mixtures compared to diesel is explained by its higher cetane number [79]. Moreover, Sivalakshmi et al. [80] explained that low molecular weight gaseous compounds degraded from biodiesel during injection into an engine cylinder at high temperatures can ignite earlier; thereby reducing ignition delay phase and accelerating the onset of biofuel combustion.

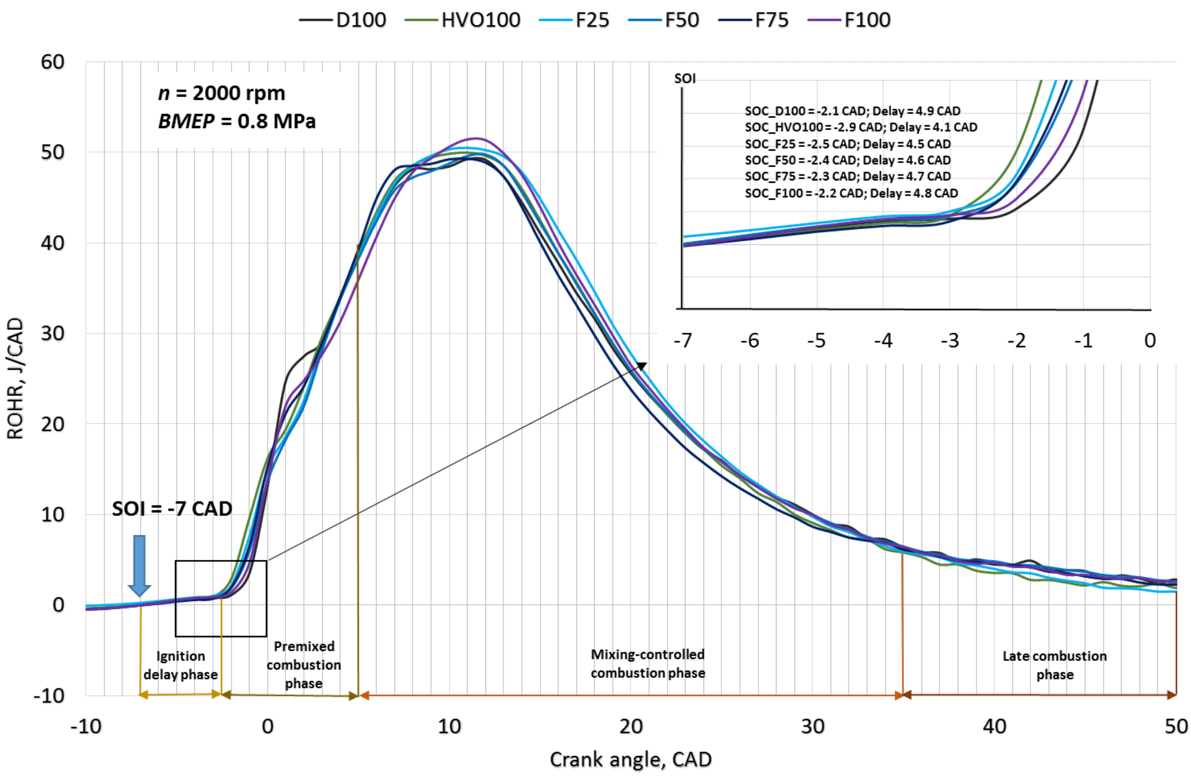

Figure 3. Dependence of the rate of heat release in the cylinder using different fuels.

At high engine load (BMEP = 0.8 MPa), the amount of fuel consumed increases in the order of HVO100, D100, F25, F50, F75, and F100 due to the lower calorific value of the mixtures compared to diesel (Table 1). An increase in the mass of injected fuel occurs, which leads to an increase temperature rise in the combustion chamber (Figure 4). Adding more fat to the HVO increases the mass of fuel injected, which leads to a delay in ignition, which is associated with a large consumption of heat for the evaporation of fuel droplets.

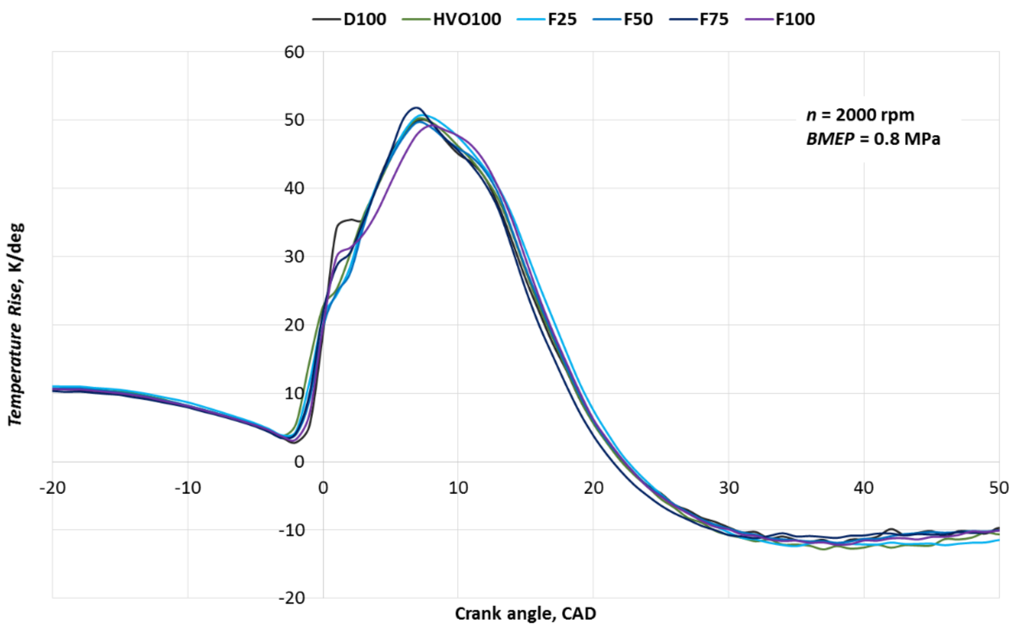

Figure 4. Dependence of the temperature rise in the cylinder using different fuels.

Furthermore, in having a shorter ignition delay, less fuel for the samples of fuel is burned in the premix mode and more during the mixing-controlled combustion phase. A decrease in the ignition delay phase for HVO, in comparison to mineral fuel, will lead to a reduced part of fuel that burns during the flash period (premixed combustion phase), and accordingly, the proportion of fuel burned in the time period of diffusion combustion will increase (mixing-controlled combustion phase).

One of the important factors causing such differences in the combustion process is the viscosity of the fuels. Table 1 shows that the viscosity of HVO is 20% less than the diesel fuel. The addition of duck fat to the fuel mixture causes a significant increase in the fuel viscosity and the ignition delay. Thus, the correlation between the viscosity of the fuel and the ignition delay phase is visible.

As can be seen from the data presented in Figure 3, for HVO the first ROHR peak corresponding to the premixed combustion phase is about 20–25% lower than for diesel fuel, and this peak is reached 1 degree earlier. This regularity can be explained by a reduced ignition delay phase, and consequently, by a smaller amount of fuel that enters the diesel cylinder during this period of time. The addition of duck fat to the fuel causes an increase in the ignition delay phase and an increase in the intensity of the combustion process during the premixed combustion phase.

The regularity described above causes a reduction in the proportion of fuel that burns out over the ignition delay phase, and consequently, an increase in the proportion of fuel that burns during the mixing-controlled combustion phase with an increase in the concentration of animal fat in the fuel mixture. This is clearly seen from the data presented in Figure 3—the maximum ROHR level in the "mixing-controlled combustion phase" (Crank angle 11–12 CAD) for pure diesel fuel is the smallest of all the presented samples. With an increase in the concentration of fat (duck fat) in the fuel mixture, an increase in the level of the maximum ROHR in the "mixing-controlled combustion phase" is observed. For F100 fuel, the maximum ROHR level during the mixing-controlled combustion phase is the highest, which confirms the described tendency.

As the percentage of fat in the mixtures increased, the ignition delay phase increased; thereby increasing the peak rate of heat release. A longer ignition delay phase was observed with the F100 mixture than with HVO and other mixtures.

It was found that the ignition delay phase for pure HVO and mixtures with pure fat is lower in contrast to diesel fuel. A possible explanation is the higher cetane number for pure HVO [81]. The higher the amount of cetanes, the shorter the ignition time. The amount of cetanes increases with the length of the unbranched carbon chain. Therefore, the lower the content of "harmful" aromatic hydrocarbons in the fuel, the higher the cetane number will be [82].

During the combustion phase, including a premix at 2 CAD, the rate of heat release for HVO is ~21% less than for D100. It should also be noted that the ignition delay phase also depends on the viscosity and density of the test mixture samples. Since HVO has a lower viscosity than diesel, this, in turn, contributes to better mixing in the premix phase. Furthermore, due to the fact that the HVO has a chain with paraffinic hydrocarbon which decomposes and evaporates faster, this contributes to a more intensive mixing with the ambient air in comparison with diesel fuel. The fat increases the viscosity of the mixture with HVO, and increases in the ignition delay phase and ROHR in the premix combustion phase approaches that of diesel. The variance between the heat release rate in 1 CAD for F25 is ~24%, F50 is ~26%, F75 is ~14%, and F100 is ~10% compared to fossil fuel.

Examining the mixing-controlled combustion phase the maximum rate of heat release for D100 (at 10–12 CAD) was ~1.2% less than for HVO100 (at 11 CAD). Furthermore, comparing mixtures with pure fat, we observed that for F100 the maximum heat release is ~4.5% higher compared to fossil fuel; for F25, F50, and F75 the results were ~2.5%, 0.7%, and 0.8%.

In Figure 4, the maximum temperature rise at the premixed combustion phase observed for diesel fuel was 1–2 CAD—34 K/deg. When the temperature rise for D and for HVO was compared, it was found that diesel fuel had a higher rate at ~26% as compared to HVO. The HVO mixtures with pure fat and the premixed combustion phase temperature rise show a related trend as compared to fossil fuel. For F25, F50, F75, and F100, they were smaller than that for diesel: ~28%, ~27%, ~16%, and ~12%, respectively. This effect may be due to the higher viscosity, later start of combustion, longer fuel injection, higher injection pressure, and velocity along with lower heating value. The intense combustion in the premix phase that influences the formation of NO_x should also be noted. Thus, the rate of formation of nitrogen oxide for mineral fuel will be higher compared to other mixtures.

In Figure 5, it was found when testing diesel fuel the pressure rise at 2 CAD (premixed combustion phase) was higher ~28% compared with HVO. Similar results were obtained for other blends. For F25, F50, F75, and F100 they were accordingly, ~20%, ~34%, ~26%, and ~14% less compared to diesel fuel. The pressure rise correlates with ROHR and the temperature rise in the cylinder. During the mixing-controlled combustion phase, the minimum pressure rise fixed using pure fat F100. This was due to the decreased fuel injection rate due to the high viscosity.

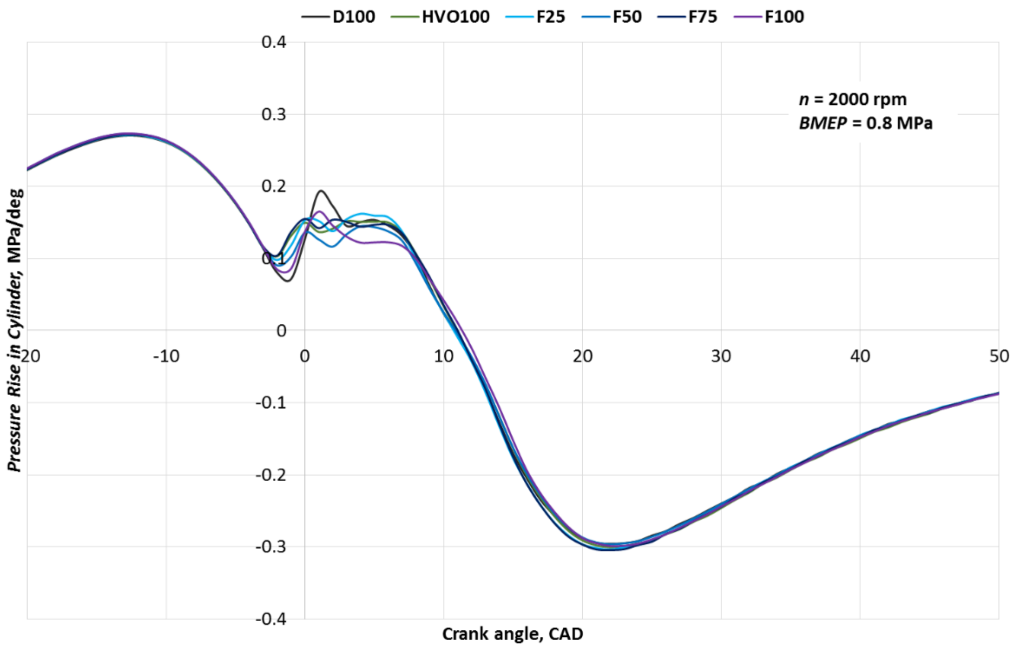

Figure 5. Dependence of the pressure rise in the cylinder using different fuels.

Peak pressure varies little, but pressure at the end of compression and start of combustion is higher with added fat (Figure 6). This means that the burning of fat is longer. The longer combustion duration was determined due to the higher consumption (lower LHV), the longer injection duration, which was further increased by the higher fuel viscosity. Exhaust gas flow energy became higher and this increased the turbocharger pressure. However, longer combustion duration of fat reduced the BTE.

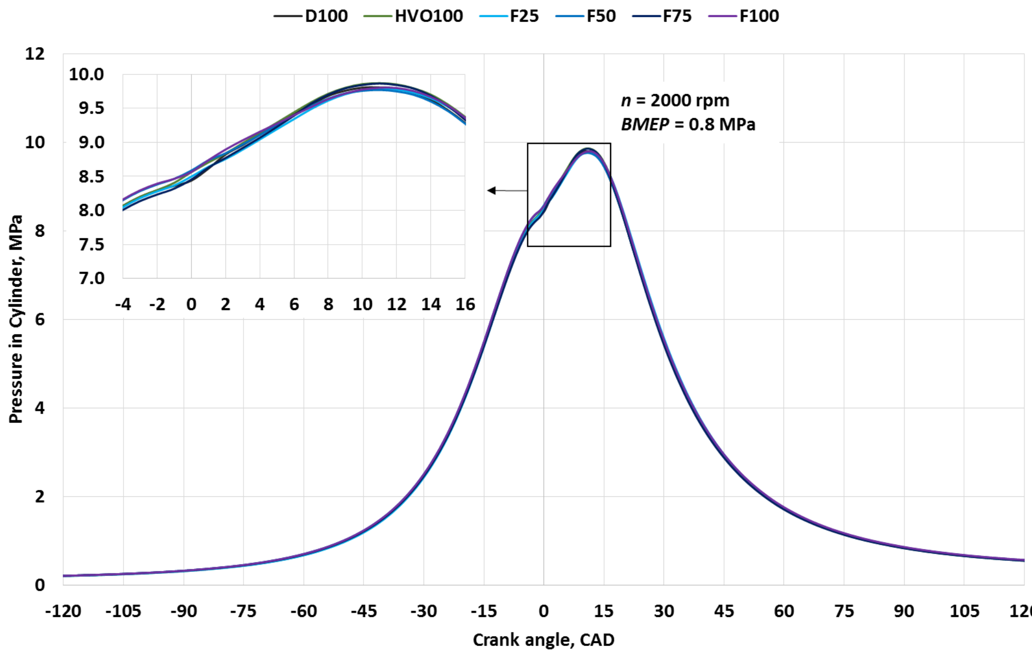

Figure 6. Dependence of the pressure in the cylinder using different fuels.

Figure 6 shows the pressure in the cylinder when BMEP = 0.8 MPa. We do not see any significant pressure differences because, for all fuel mixtures, the start of the fuel injection is the same (SOI = 7 BTDC), there is no very significant difference in fuel properties, and the engine load is the same. However, after performing the analysis of the combustion process (using these pressures), we see more pronounced differences in the various combustion indicators (Figures 3–5) when the studied fuel mixtures are used.

Higher maximum cylinder pressures were observed when the engine was running on diesel. This resulted in the longest ignition delay phase, maximum ROHR, temperature rise, and pressure rise in the premixed combustion phase. The maximum cylinder pressure was slightly reduced with the use of HVO and fat mixtures.

3.2. Ecological Indicators

3.2.1. Emissions of Carbon Dioxide (CO_2)

Specific CO_2 emissions, that are shown Figure 7, decrease for all samples of fuel with growth in the load. The BMEP = 0.8 MPa for HVO emissions of carbon dioxide were ~4.6% lower compared with fossil fuel. Furthermore, a decrease in CO_2 for F25 and F50 ~ 3.2% and 1.7% appropriately, was established. For F75 and F100, the CO_2 emissions were on average ~0.9% and ~2.1% higher compared with fossil fuel. The higher rates of CO_2 in the mixtures are because of the higher carbon and oxygen content of the examined fuels in comparison with mineral fuel and due to higher fuel consumption.

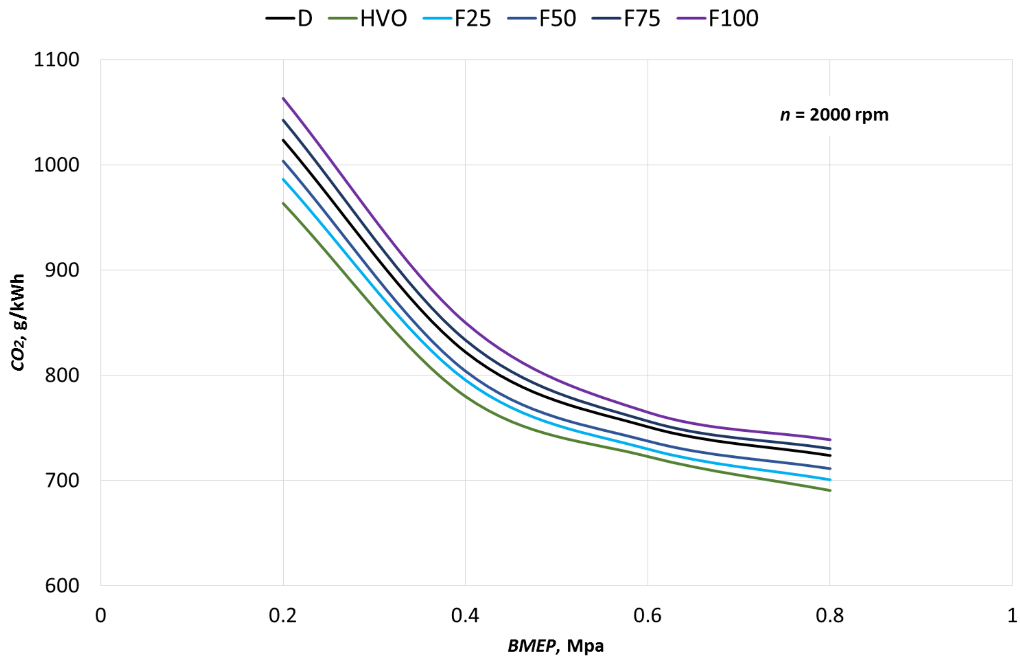

Figure 7. Dependence of carbon dioxide emissions on the load using different fuels.

Additionally, in the time of testing, it was found that blends that have a smaller ratio of C/H contribute the most to CO_2 reduction (Table 1). HVO, in turn, has a smaller ratio of C/H (5.7%), which allows for the reduction of CO_2 for this fuel sample compared to the mixtures and fossil fuel. With decreasing emissions of CO_2 less fuel consumption was noted. Perhaps the lack of air in the mixture of F25 and F50 slows down the combustion process, and thus reduces the production of CO_2 compared to D100, F75, and F100. The rate of the combustion process has little effect on the level of CO_2 formation. Several factors prevail: specific fuel consumption and specific carbon content in the fuel.

The level of specific CO_2 emissions of diesel exhaust gases for different fuels (Figure 7) at the same load is directly proportional to the specific fuel consumption and is directly proportional to the percentage of carbon in the fuel. It can be seen from Table 1 that with an increase in the concentration of fat (duck fat) in the fuel mixture, the percentage of carbon in the fuel decreases, but at the same time, the lower specific heat of combustion of the fuel also decreases, which causes an increase in specific fuel consumption. That is, the influence of the above factors on the level of CO_2 emissions with exhaust gases is opposite. Consequently, the final effect of fuel on the level of CO_2 emissions from the exhaust gases is determined by which of the two factors will dominate over the other.

So, for F75 and F100 fuels, an increase in the specific fuel consumption by an average of 12–18%, respectively, is the dominant factor over a 7–9% decrease in the specific carbon content in the fuel. As a consequence, there is an increase in specific CO_2 emissions for F75 and F100 fuels in comparison to diesel fuel throughout the entire range of engine operating loads. For HVO, F25, and F50 fuels, a decrease of 7%, 5%, and 3%, respectively, of the carbon content in the fuel is the dominant factor over the change in the average specific fuel consumption. As a consequence, for these fuels, a decrease in the specific CO_2 emission is observed over the entire load range.

3.2.2. Emissions of Carbon Monoxide (CO)

Since the fuel is split into CO at the time of the combustion process and then oxidized to carbon dioxide, the amount of CO tends to reduce with the growing temperature. The presence of hydrogen-containing substances, such as hydrogen, accelerates this process [83]. Moreover, pure fat blends are oxygenated fuel and the extra oxygen molecule helps the fuel burn better, which helps lower CO emissions.

With an increase in the concentration of fat (duck fat) in the mixture, the viscosity of the fuel increases, and also the specific net calorific value decreases (Table 1). A decrease in the specific net calorific value causes an increase in the cycle fuel supply. Both of these factors cause an increase in the maximum fuel injection pressure, and that can decrease the average diameter of fuel droplets in the cylinder and improve the distribution of fuel to the periphery of the combustion chamber. In turn, a decrease in the average diameter of fuel droplets has a positive effect on the completeness of fuel combustion, and an improvement in the distribution of fuel droplets to the periphery of the combustion chamber contributes to the elimination of zones with low local oxygen deficiency, which also reduces the formation of CO. However, with a significant increase in fuel viscosity, this effect of reducing CO emissions may not be achieved and pollutant emissions may increase.

Thus, at low load (BMEP = 0.2 MPa), the CO emission of F100 is ~160% higher compared to fossil diesel fuel (Figure 8). This indicates incomplete burning of fuel that consists of pure fat. A low cycle rate results in a low pressure, which, in turn, causes the formation of large droplets of high density and viscosity fuel, which burn much worse. The same trend was noticed for all HVO and fat blends. By increasing the load to BMEP = 0.4 MPa, the maximum difference of emissions for F100 and diesel fuel was ~63%. By increasing the load to BMEP = 0.6 MPa and BMEP = 0.8 MPa, the CO emissions of all fuel mixtures became similar.

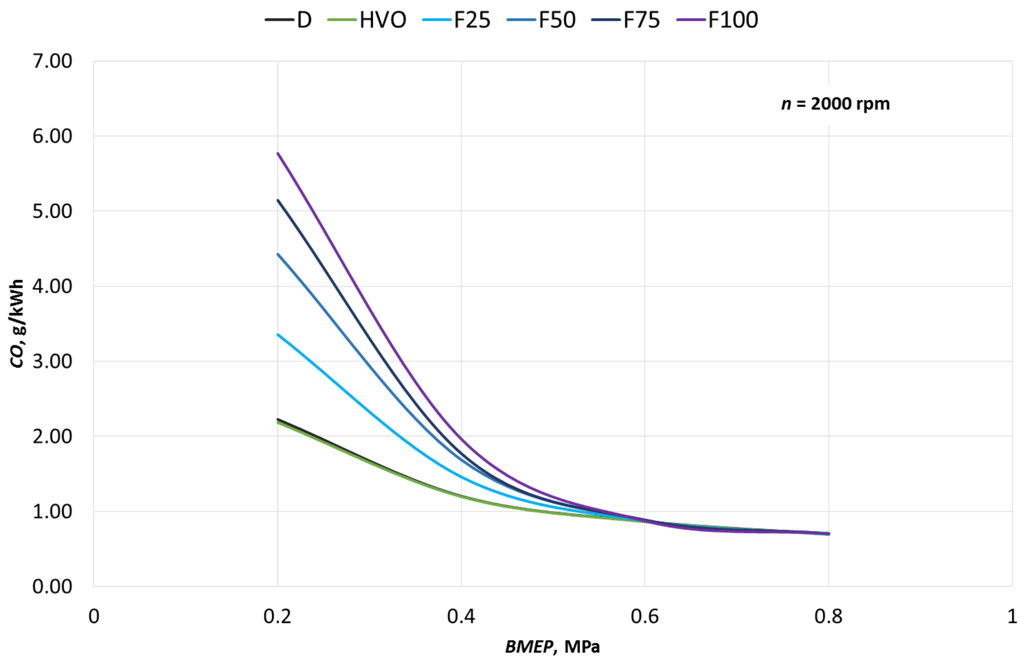

Figure 8. Dependence of carbon monoxide emissions on the load using different fuels.

3.2.3. Emissions of Hydrocarbons (HC)

As can be seen from the Figure 9, at all loads the mixtures have lower HC values, unlike mineral fuel, and for HVO this indicator is the smallest. The high-rise cetane number of HVO, and thus of blends with HVO, reduces hydrocarbon exhaust gases in comparison to diesel fuel [84]. That is due to the low content of aromatic compounds in the fuel mixtures. Furthermore, it should be noted that the fuel mixture with duck fat contains some oxygen in the structure, so it improves the fuel combustion process, and HC emissions will be reduced when using these blends with a percentage of pure fat.

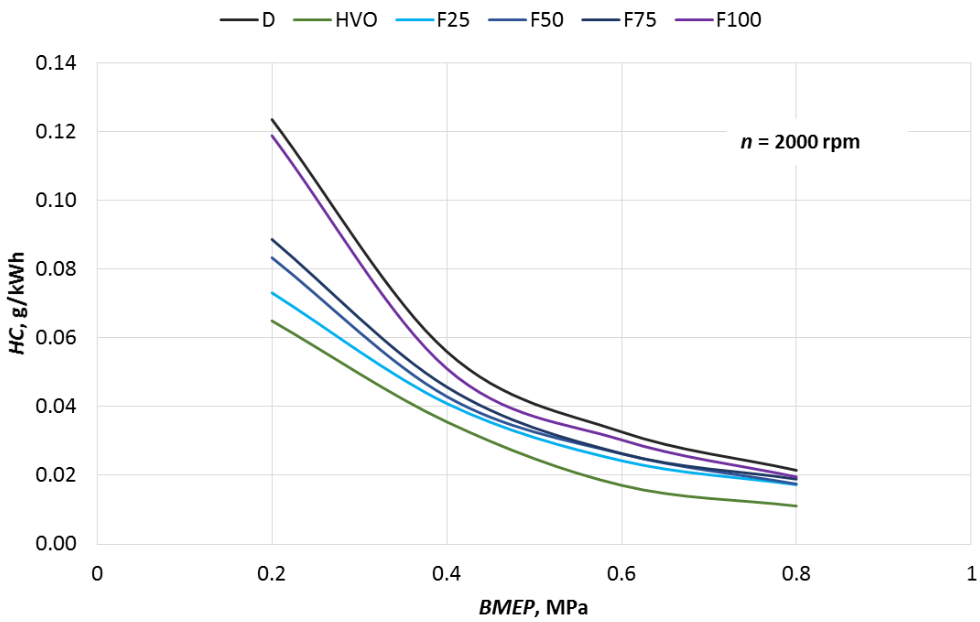

Figure 9. Dependence of hydrocarbon emissions on the load using different fuels.

For example, F100 for BMEP = 0.2 MPa has ~4% less HC emissions than D, while HVO has ~ 47% less, opposite with diesel fuel. At higher loads, a similar trend was determined for all fuel samples. On average, the HC values for the combinations F25, F50, F75, and F100 were lower, opposite to fossil diesel fuel, respectively, ~28%, ~23%, ~19%, and ~7%. HC emissions from HVO fuel at higher engine loads are ~45% lower compared to diesel. This can be explained by the above-discussed influence of fuel on the quality of the atomization and combustion processes. In case the fuel has a lower cetane number, it takes longer to start, which causes higher HC emissions [85].

3.2.4. Smoke

Smoke is generated by partial combustion of the fuel. The HVO smoke levels that we see in the graph (Figure 10) are reduced by an average of ~18% compared to diesel. This can be explained by the fact that the C/H ratio in HVO in its composition was 17% less (Table 1), and also does not have such components as sulfur, aromatic hydrocarbons, and other mineral impurities in its chemical composition, which form the formation of soot [86]. As discussed earlier, testing mixtures with duck fat (Table 1) contains some oxygen in its molecule, which improves combustion. Blends of HVO and pure fat have lower values in comparison with diesel fuel. The average values for all tested loads were: for F25~51%, F50~54%, F75~56%, and F100~59%. The decrease in smoke emission for the mixtures can be explained by the high mass oxygen content and the lower C/H ratio (Table 1). The presence of excess oxygen in mixtures with pure fat leads to better combustion and results in less smoke generation under all engine load conditions.

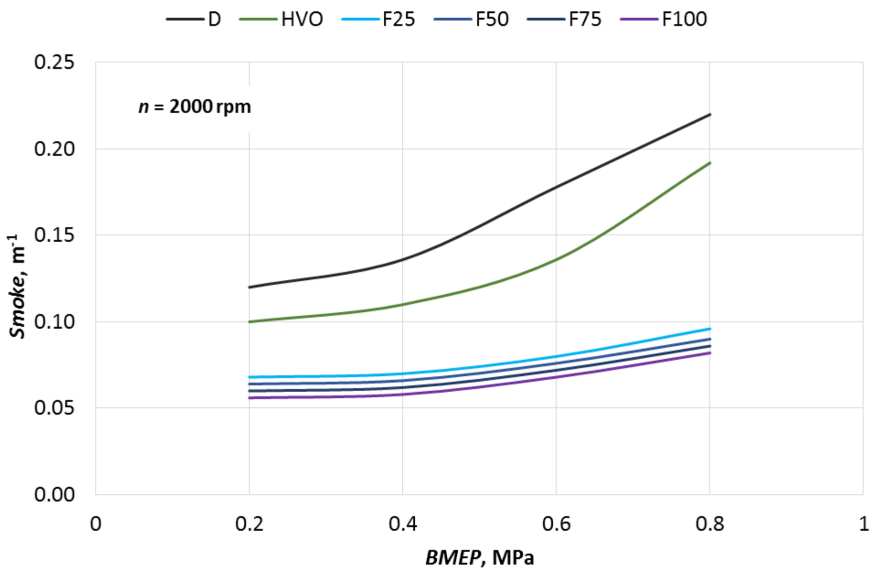

Figure 10. Dependence of smoke emissions on the load using different fuels.

3.2.5. Emissions of Nitrogen Oxide (NO_x)

Figure 11 shows increasing NO_x emissions with increasing loads for all testing fuels. This was due to the higher combustion temperature. D100 has the highest NO_x emissions. Furthermore, the variation between D100 and HVO100 to various loads on average is ~18%, and between D100 and F100, ~5%. At a higher load (BMEP = 0.8 MPa), the NO_x emissions were reduced for HVO~17.6%, F25~9.1%, F50~7.2%, F75~5.4%, and F100~3%, than for D100. This means that NO_x emissions from conventional diesel are highest in all cases. Nitrogen oxide emissions are lowest with HVO, which has the highest CN count of all samples. The ambiguous impact on nitrogen oxide emissions may depend on the cumulative effects of ignition delay, fuel injection quantity, and injection quantity distribution between the pilot and main injection [62]. Ignition quality is often influenced by cetane number; therefore, a high CN value indicates a short ignition delay, which means less fuel energy (ROHR) in the premix stage, and therefore, lower NO_x emissions.

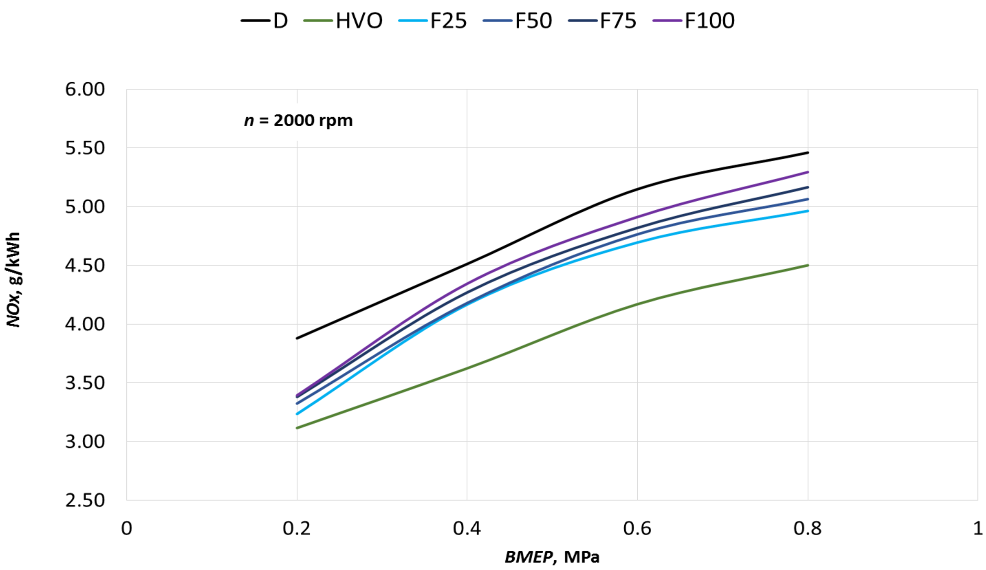

Figure 11. Dependence of nitrogen oxide emissions on the load using different fuels.

It can be assumed that the emissions grow for HVO–fat mixtures is related to the presence of oxygen molecules in the fuel. The increase of NO_x emissions can also be explained by an increase in the iodine value. The amount of iodine is related to the cetane number, and the density and compressibility of fuel samples [87]. Thus, the experimental pure fat mixtures improve the oxidation of the fuel during combustion, leading to a higher local temperature, and therefore, a rise in nitrogen oxide emissions.

3.3. Energy Indicators

As presented in Figure 12, the brake specific fuel consumption (BSFC, g/kWh) for all duck fat blends at high loads was higher compared with pure diesel. However, the BSFC for HVO was lower by ~2.4% in comparison with pure diesel. It was noted that with an increase in the percent of pure fat in the samples, the fuel consumption rose for F100 ~ 17.7% in comparison to diesel fuel. When comparing fossil diesel fuel and other HVO mixtures with pure fat, an increase in BSFC for F25 ~ 1.6%, F50 ~ 6.8%, and F75 ~ 11.8% was noted. On condition that the calorific value of fat has a low value, then to maintain a constant speed at a certain load, the engine needs, accordingly, more fuel, and hence, we have an increased consumption of fuel [88]. One of the reasons that may influence the increase in BSFC with a percentage of pure fat is associated with a higher density compared to fossil fuels [89].

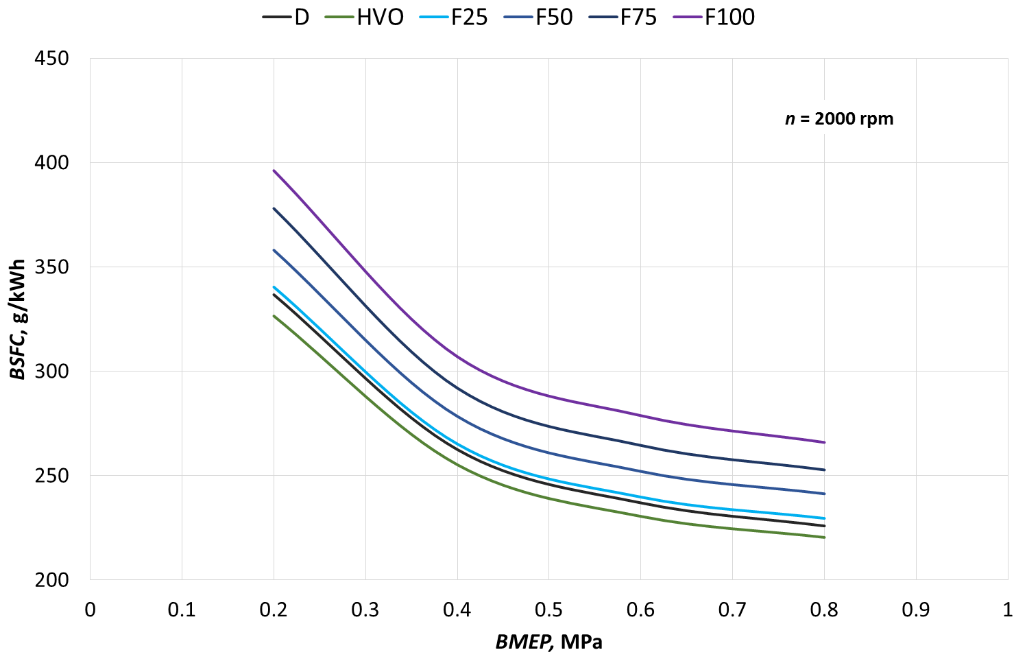

Figure 12. Dependence of BSFC, g/kWh on the load using different fuels.

Figure 13 presents that, for all samples of fuel, BTE was increased with increasing load, due to a rise in the ratio of indicated power and internal mechanical losses of the engine. With an increase in the load, the quality of the processes of mixture formation and fuel combustion improves as the combustion temperature rises [90], which also determines the above-described dependence of the BTE on the engine load.

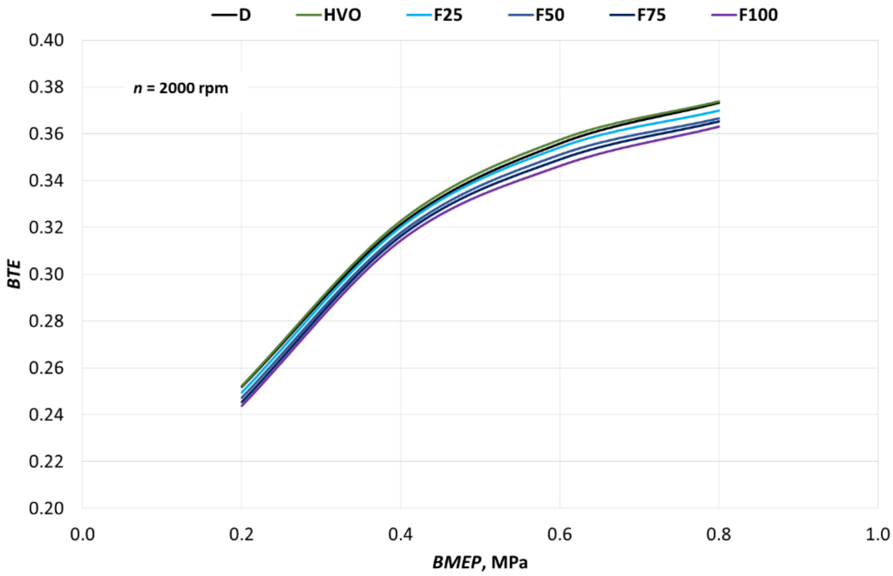

Figure 13. Dependence of BTE on the load using different fuels.

Figure 13 shows the highest BTE for HVO, followed by mineral diesel fuels. The contrast between these samples of fuels was ~0.14%, which is directly related to LHV and the combustion process. A total of 1 kg of HVO fuel has ~2.4% more energy and HVO cyclic fuel mass is ~2.4% less compared to diesel. HVO fuels have shorter injection duration and shorter combustion duration. Lower cooling and exhaust heat losses increase the BTE of HVO in comparison to diesel fuel.

There is a clear trend in Figure 13 that as the pure fat in the blends increases, the BTE tends to decrease. At loads of BMEP = 0.8 MPa for F100 it was found that a reduction of BTE was on average ~2.7%, compared to diesel fuel. Brake thermal efficiency depends on how efficient the combustion is. The amount of oxygen in the fuel with the duck fat additive increases, this reduces the LHV and requires longer fuel injection duration. The BTE tends to decrease, since poor atomization is important due to the high viscosity of fat. With longer combustion duration, more energy of fuel is transferred to the cooling system and to the exhaust, which reduces the BTE. Higher amounts of oxygen, which accelerates combustion, have a smaller effect here.

4. Conclusions

On the basis of the studies carried out, it can be concluded that:

1. The HVO compared to diesel fuel has ~1 CAD shorter ignition delay, ~20% lower ROHR during the premixed combustion phase, and slightly higher ROHR during the mixing-controlled combustion phase. The addition of pure fat to the mixtures increased the ignition delay phase compared to HVO, causing a shorter period of the premixed combustion phase and increasing ROHR at same time, but did not reach the level of diesel;
2. CO_2 emissions at all engine loads were reduced for HVO ~ 7% for F25 and F50 mixtures approximately by 3–5%, except F75 and F100, which were ~1.2% and ~2.8% higher than diesel fuel. This is mainly due to the specific fuel consumption and C/H ratio in fuels, as well as the efficiency of the mixing and combustion processes;
3. CO emission at a low load for F100 increased by 160–60% compared to diesel fuel. The reason for this is a low fuel pressure, which, in turn, causes the formation of large droplets of high density and viscosity fuel, which burn much worse. Increasing the engine load significantly reduces the CO emissions of pure fat. HC emissions for HVO100, F25, F50, F75, and F100 were lower, opposite to fossil diesel fuel, respectively, ~45%, ~28%, ~23%, ~19%, and ~7%. This is explained by the simpler molecular

structure of HVO and better injection and combustion properties. The fat changes the quality of the injection and the combustion deteriorates, especially at low loads;
4. Smoke values, on average, decreased by 18% for HVO and 51%, 54%, 56%, and 59% for F25, F50, F75, and F100 compared to diesel fuel. The decrease in smoke emission for the mixtures can be explained by the high mass oxygen content in duck fat and the lower C/H ratio in HVO. Due to the fat additive, the worst fuel injection did not increase the smoke;
5. The maximum difference of NO_x emissions was observed between D and HVO and amounted to ~18%. By increasing to F100 emission of NO_x, it remained 6% lower compared to diesel. It can be assumed that the maximum temperature rise during the combustion of diesel fuel is higher; therefore, the level of formation of nitrogen oxides for diesel is higher. Due to the worst fat injection, the maximum combustion temperature was lower compared to diesel;
6. BSFC of pure HVO fuel was ~2.4% lower compared to conventional diesel due to 2.4% higher LHV. HVO fuel mixtures with a duck fat additive can only be used after heating them to 40–50 °C. With an increase in the concentration of fat to 100% in the HVO–fat mixtures, a proportional increase in the BSFC was observed on average up to 17.5% in comparison with conventional fossil diesel fuel due to the ~13% lower calorific value of the fat and slightly (2–3%) lower BTE for fat containing mixtures, due to their higher viscosity, and accordingly, poor atomization and combustion compared to diesel fuel.

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