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METHODS

Carbon emissions modeling for smarter carbon footprint decisions: A systematic review

Ovundah King Wofuru-Nyenke*

Department of Mechanical Engineering, Faculty of Engineering, Rivers State University, Port Harcourt, Nigeria

***Correspondence:**
Ovundah King Wofuru-Nyenke,
ovundah.wofuru-nyenke@ust.edu.ng

ORCID:
Ovundah King Wofuru-Nyenke,
0000-0003-2087-6918

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Climate change and environmental deterioration due to greenhouse gas emissions are a major concern around the globe today. This article aims to highlight how various authors have carried out carbon emissions modeling for smarter carbon footprint management and also proffer solutions to the greenhouse gas emissions issue, which is giving rise to global warming and natural disasters across the globe. This study makes use of the Systematic Literature Review (SLR) methodology for identifying, analyzing, and synthesizing articles published from 2015 to 2020, a period of 6 years, on the topic of carbon emissions modeling. The SLR results indicated that there has been a rising interest in the issue of carbon emissions from the period of 2015 to 2020, as seen by the evolution of publications in the area. This can be explained by the increased incidence of natural disasters occurring as a result of the global warming phenomenon due to greenhouse gas emissions. The various ways in which different models have been used for carbon emission analysis and management have been described, while explaining various means by which greenhouse gas emissions can be curtailed to stop the alarming rate of global warming and maintain a sustainable and habitable planet for all.

Keywords: carbon, emissions, modeling, greenhouse gases, systematic review

1. Introduction

Emissions from greenhouse gases are the main reasons for the increasing number of extreme climate conditions and changes across the world. As a result of this, nations are making progressive moves to more predominantly utilize renewable energy sources in order to be carbon emissions neutral, reduce reliance on fossil fuels for electricity generation and transportation, and positively impact the environment. Greenhouse gases are gases that are responsible for the greenhouse effect, which occurs as a result of infrared radiation absorption (1). Therefore, these gases basically trap heat or infrared radiation preventing the heat from escaping into outer space, thereby leading to global warming of the atmosphere. The main greenhouse gases which are increasing in concentrations are hydrofluorocarbons (HFCs), carbon dioxide (CO_2), hydrochlorofluorocarbons (HCFCs), nitrous oxide (N_2O), and methane (CH_4).

Consumption of fossil energy and production of cement account for most of the carbon emissions from human activities, giving rise to approximately 80% of the overall greenhouse gas emissions from activities of humans (2). China is one of the largest consumers of fossil energy in the world and hence one of the largest CO_2 emitters (3). The repercussion of this is the change in climate of the country, leading to increase in sea levels and displacement of people within the country, natural disasters, and economic losses (4). As a result of this, the country faces great pressure to decrease emissions and achieve neutrality from the international community. It is believed that there will be crises related to the climate and environment in the future decades if there is continuity in the global warming trend. Therefore, it is necessary to develop models for managing carbon emissions and achieving carbon neutrality to reduce change in climate and attain sustainable development goals across the world.

This work aims to highlight how various authors have carried out carbon emissions modeling for smarter carbon footprint management and also proffer solutions to the greenhouse gas emissions issue, which is giving rise to global warming and natural disasters across the globe. The study makes use of the Systematic Literature Review (SLR) methodology in identifying, analyzing, and synthesizing articles published between from 2015 to 2020, a period of 6 years, on the topic of carbon emissions modeling. The SLR methodology is basically concerned with finding, choosing, and critically appraising publications so as to provide answers to formulated questions. The various ways in which different models have been used for carbon emission analysis and management have been described, while explaining various means by which greenhouse gas emissions can be curtailed to stop the alarming rate of global warming and maintain a sustainable and habitable planet for all.

2. Methodology

This research utilizes the Systematic Literature Review (SLR) method to evaluate several scholarly publications that have been peer reviewed and published between 2015 and 2020 and are related to the "Carbon Emissions Modeling for Smarter Carbon Footprint Decisions:. The SLR methodology is basically concerned with finding, choosing, and critically appraising publications in order to provide answers to the research questions that have been formulated (5). The phases of developing an SLR involve formulating research questions, locating the publications, selecting and evaluating publications, analyzing and synthesizing the publications, and utilization and reporting of the results. **Figure 1** shows the various phases of developing an SLR and how they are connected.

The following subsections briefly discuss these five phases:

2.1. Research questions formulation

Research questions formulation constitutes the initial stage in conducting SLRs. Appropriate formulation of a research question was conducted in this stage to provide a theme to concentrate on as well as guidance for the study. Therefore, the study was aimed at providing answers to the research question. The research question that was formulated is as follows:

- What is the trend in carbon emissions modeling between year 2015 and year 2020?

The question was so formulated so as to propose a carbon emissions management model. This question seeks to investigate and understand the carbon emissions modeling approaches that have been utilized in analyzing and managing carbon emissions between year 2015 and year 2020.

2.2. Locating publications

Locating publications constitutes the second stage of the SLR methodology. In this stage, online databases such as Google Scholar, ScienceDirect, Taylor & Francis Online, SpringerLink, IEEE Xplore, Emerald Insight, and Wiley Online Library were searched for publications related to greenhouse gas emissions models. The terms and words that were utilized for the search include "Carbon emissions modeling," "Autoregressive distributed lag carbon emissions models," "Vector error-correction carbon emissions models," "Stochastic impact by regression on population, affluence and technology carbon emissions models," "Artificial intelligence carbon emissions models," "Simultaneous equations carbon emissions models," "Regression carbon emissions models," and "Data envelopment analysis carbon emissions models." The search terms were precise enough to produce only publications related to greenhouse gas emissions models in various search engines. Terms for the search were chosen in such a way that they were encompassing enough to represent the main ideas behind the study.

2.3. Selecting and evaluating publications

Selecting and evaluating publications constitutes third stage of the SLR and was conducted based on various criteria for inclusion in this research. One of the criteria is that each article must be a study that has been peer reviewed. Another inclusion criterion is that the research must have been published between 2015 and 2020 and must propose a model for carbon emissions modeling. Also, the paper must have been written in English language as it is the most popular language for developing scientific articles (6–8). An overall quantity of 216 papers were identified by applying these criteria, and 102 papers were discovered to be duplicates and

FIGURE 1 | Phases of SLR.

hence removed from the study. This left 114 papers in total for use in this study.

2.4. Analysis and synthesis of publications

Analysis and synthesis of the publications constitutes the penultimate stage of the SLR process. Analysis is concerned with individualizing parts of a study and explaining how these parts are related. On the other hand, synthesis is concerned with discovering connections between component parts of various studies selected. Each article was analyzed in this stage based on the modeling and optimization technique utilized, journal of publication of the article, and year of publication. During synthesis, connections between the specific features of the various selected studies was made.

2.5. Results utilization and reporting

Results utilization and reporting is the last stage of the SLR process. This stage summarizes all articles that have been selected, in consideration of the data extracted from the articles. All knowledge, unknowns, and results are described in this stage, and the information is presented using graphs, statistics, and tables. This stage basically presents the final results of the analysis and synthesis of the literature review.

3. Results

This section presents the main findings of the SLR conducted. The main findings of the research were the discovery of various models used for analyzing and exploring the effect of greenhouse gas emissions on the global climate. The following sections describe the various kinds of models that have been used for carbon emissions analysis, modeling, and management.

3.1. Autoregressive distributed lag models

A number of scholars have used autoregressive distributed lag (ARDL) models for carbon emission analysis. Koengkan and Fuinhas (9) presented a panel autoregressive distributed lags (PARDL) model for investigating how transition to renewable energy affects CO_2 emissions of Caribbean and Latin American countries. Their research indicated that the energy transition process can lessen degradation of the environment in Latin America and Caribbean countries. Similarly, Adedoyin and Bekun (10) utilized a fully modified ordinary least square and pooled mean ARDL model for studying carbon emissions, real gross domestic product (RGDP) per capita, and tourism. The research indicated that tourism responds positively to sudden changes in urbanization throughout various periods. Also, Shoaib et al. (11) used ARDL modeling for conducting a comparison analysis of countries in various stages of development to determine the financial development impact on carbon emissions. The results of the research showed that being financially developed majorly affects carbon emission positively in the long run. Dat (12) applied the ARDL cointegration modeling approach to study the growth of the economy, consumption of energy, and emissions in Indonesia. The findings of the research revealed that economic growth and emissions can be predicted by consumption of energy in Indonesia. In the same vein, Cosmas et al. (13) employed various ARDL models for analyzing the macroeconomic causes of emissions in Nigeria. The results showed that changes in GDP per capita resulted in high magnitudes of impacts on carbon emissions. Similarly, Akadiri et al. (14) employed the ARDL and bounds testing models for examining the effects of heating degree days, cooling degree days, and ecological footprint on degradation of the environment over a certain period. The results of the work indicated that the heating degree days, cooling degree days, and ecological footprint accounting increase environmental degradation. Udemba (15) used linear ARDL, structural breaks, and non-linear ARDL for analyzing India's commitment in reducing emissions and enhancing environmental performance positively. The study found that there was a significant positive link between energy use, ecological footprint, and agriculture as well as population and a negative link exists between foreign direct investment and ecological footprint. Kim et al. (16) employed the directed acyclic graph technique and the ARDL model for investigating the relationship between total energy CO_2 emissions, overall biomass energy consumption, and GDP in the United States. The results indicated that there is a unidirectional causal link among overall biomass energy consumption, GDP, and overall energy carbon emissions.

Toumi and Toumi (17) applied a non-linear ARDL model for investigating asymmetries among carbon emissions, renewable energy, and RGDP in various time periods. The results revealed that negative carbon emissions shocks had only positive impacts on RGDP in the long run but are not observable in the short run. Similarly, Akalpler and Hove (18) applied an ARDL model for analyzing the effects of energy use, carbon emissions, gross fixed capital formation, exports and imports, and RGDP per capita on Indian economic growth. The results revealed that depending of the period, RGDP per capita is influenced by previous values, gross fixed capital formation, consumption of energy, carbon emissions and imports, and gross fixed capital formation and exports. Leal et al. (19) utilized an ARDL model for investigating how economic growth is affected by carbon emissions, fossil fuels, and consumption of renewable energy in Australia. The results indicated that increased GDP in Australia increased investment in renewable energy sources, although there is limited renewable energy technology, which leads to negligible impact on reducing carbon intensity in the long term. Sun et al. (20) used the ARDL model for investigating how valid the pollution haven hypothesis is in China. The results indicated that the pollution haven hypothesis exists in China. Cherni and Jouini (21) employed an ARDL model for studying how carbon emissions, consumption of renewable energy, and growth of the economy are related in Tunisia. The results indicated that to achieve success in energy transition projects as well as benefits from positive impacts on environment protection and economic growth, there has to be adoption of strategies which encourage renewable energy. Riti et al. (22) used the ARDL model for studying the connection between carbon emissions, growth of the economy, and consumption of energy. It was revealed that China's environmental Kuznets curve turning point is inconsistent with the turning points obtained from other studies, and sensitivity of the result to variables selection, various data sources, various pollutants, and scope of the data is the main reason for the inconsistencies. Ben Jebli (23) employed the ARDL approach for examining the short-term and long-term relationships between waste consumption, health indicators, combustible renewables, RGDP, rail transport, and carbon emissions in Tunisia. The study showed a relationship among the various variables in the long term. Bölük and Mert (24) used ARDL modeling to examine the potential of renewable energy sources in reducing greenhouse gas emissions impact in Turkey. The results indicated that the renewable sources electricity production coefficient with respect to emissions of carbon is significant and negative in the long term.

3.2. Vector error-correction models

Selvanathan et al. (25) utilized the ARDL, vector error-correction model (VECM), and panel frameworks to study the interrelationship between energy consumption, tourism, GDP, and carbon emissions in South Asia. The results revealed that tourism positively affects GDP, carbon emissions, and energy demand in the long term. Similarly, Lee and Yu (26) used time-series panel vector autoregression modeling for analyzing the interconnection among costs of energy, energy usage, renewable energy shares, greenhouse gas emissions, and economic growth in the industrial sector of Korea. The results revealed that increased consumption of energy by large firms has a significant negative impact on costs of energy and greenhouse gas emissions compared to smaller, medium-sized enterprises. Ummalla and Samal (27) and Kong and Khan (28) employed the ARDL bounds testing approach to cointegration and VECM, respectively, to explore the connection between natural gas and coal consumption as well as consumption of petroleum, consumption of renewable energy, carbon emissions, and growth of the economy. The results indicated that there was a short-run bidirectional causality between renewable energy consumption and growth of the economy. Longe et al. (29) used the VECM approach to study the dynamic link between financial development and carbon emissions in Nigeria. The results revealed that in the short term and long term, financial development had a negative impact and positive impact, respectively, on the carbon emissions in Nigeria. Saudi et al. (30) applied the VECM for examining the relationship among energy consumption, economic growth, and carbon emissions in Indonesia. The results revealed that apportioning consumption energy and properly managing carbon emissions are probably going to have no antagonistic impact on the GDP per capita of the country. Mbarek et al. (31) used the VECM approach for investigating the relationship between renewable energy consumption, growth of the economy, carbon emissions, and energy consumption in Tunisia. It was discovered that economic growth affects carbon emissions in the short and long terms. Meng and Han (32) applied VECM for investigating the connection between economy, transport infrastructure, environment, and population. The results indicated that road infrastructure development hardly contributes to the GDP growth in the transport sector but caused a direct increase in population density and transport carbon emissions. Jebli and Youssef (33) used the VECM for studying the short- and long-term nexus among renewable and non-renewable energy consumption, per capita carbon emissions, RGDP, trade openness ratio, and agricultural value added in Tunisia. The results revealed that increasing international economic exchanges provides opportunities to the agricultural sector to thrive and benefit from renewable energy technology transfer. Chen et al. (34) used panel cointegration and VECM to model the relationships among economic growth, carbon emissions, and energy consumption. The results indicated that energy consumption negatively affects GDP. Asumadu-Sarkodie and Owusu (35) used VECM for analyzing factors such as carbon dioxide emissions, total primary energy consumption, population, and GDP. The results showed an existence of long-run causality running from population, GDP, and total primary energy consumption to carbon emissions. Lin et al. (36) used VECM to investigate the industrial value-added impact on carbon emissions in Nigeria. The study indicated industrial value added gives rise to an inverse significant nexus with carbon emissions.

Roespinoedji et al. (37) utilized a combination of ARDL and VECM for examining the elements influencing renewable electricity consumption in Malaysia. The results indicated that financial development and foreign direct investment are the real drivers for renewable energy consumption. Similarly, Yazdi and Shakouri (38) employed the ARDL approach of cointegration test and VECM for analyzing growth of the economy and carbon emissions as well as consumption of energy and consumption of renewable energy in Germany. The results showed that hikes in renewable energy sources would incur more electricity production costs and stifle the development of the economy via the expansionary effect of the consumption by industries. Zambrano-Monserrate et al. (39) used the ARDL model and VECM to analyze the GDP and carbon dioxide emissions relationship from the overall renewable electricity consumption, consumption of energy, dry natural gas consumption, and overall petroleum consumption for Peru. The results revealed that Peru needs to urgently design environmental policies that minimize greenhouse gas emissions. Lu (40) utilized a VECM for analyzing the relationships among energy consumption, carbon emissions, trade, and economic growth in selected Asia-Pacific regions. The study indicated that Asia-Pacific regions need to utilize energy policy to reduce emissions of carbon by improving energy efficiency and utilization of more renewable energy. Baloch et al. (41) used the ARDL model and VECM for investigating the link between financial instability and carbon emissions within the multivariate framework in the Saudi Arabian economy. The results indicated that financial stability had an insignificant impact on carbon emissions. Zhao and Luo (42) utilized the ARDL model with VECM to forecast fossil energy consumption in China. The results indicated GDP and carbon intensity have a tendency to decrease as the expected energy consumption structure is achieved by the governments.

3.3. Stochastic impact by regression on population, affluence, and technology models

Song et al. (43) used the improved stochastic impact by regression on population, affluence, and technology (STIRPAT) model to study the effect of environmental infrastructure investment on carbon and SO_2 emissions. The results indicated that environmental infrastructure investment constitutes a major positive effect on mitigating carbon emissions, but its effect on SO_2 emissions fluctuated. Similarly, Wu et al. (44) employed the STIRPAT model with the panel cointegration approach for carbon emission analysis in selected regions. The results revealed that industrial structure, energy intensity, population size, and per capita GDP were the most significant factors affecting carbon emissions. Li and Wang (45) employed the STIRPAT model with spatial analysis to evaluate carbon productivity in China. The results showed that GDP per capita, technology level, foreign direct investments, and trade openness positively affected China's carbon productivity, while industrial proportion, energy consumption structure, and urbanization level negatively affected the carbon productivity of the country. Miao et al. (46) utilized the STIRPAT model to examine the key factors behind China residential carbon emissions and test the environmental Kuznets curve hypothesis. The results indicated that in the Eastern region of China, the environmental Kuznets curve is confirmed at the national level. Zhang and Zhao (47) employed the STIRPAT model for evaluating the influence of various factors on carbon emissions in China. The study indicated that research and development investment and energy cleanliness play important roles in reducing carbon emissions across the country. Ghazali and Ali (48) applied the extended STIRPAT model and the regression of group mean dynamic common correlated estimator to examine the connection between carbon emissions, affluence, population, technology, and other factors such as urban employment level, labor productivity, energy mix, energy intensity, and trade openness. The research results indicated that population, GDP per capita, and carbon emissions intensity as well as energy intensity are the main culprits of carbon emissions. Sun et al. (49) utilized an Impact, Population, Affluence and Technology (IPAT) model for evaluating 48 peak carbon emission scenarios. They discovered that maintaining a relatively high GDP growth, reducing energy intensity, and increasing consumption of non-fossil energy are the most efficient behaviors for controlling carbon emissions. Cui et al. (50) used a STIRPAT multivariate linear model to examine the relationships between net carbon emissions and some socioeconomic factors, including GDP per capita, energy intensity, population, and urbanization level. The results indicated that population, urbanization level, and GDP per capita had the highest contribution to increasing net carbon emissions, while energy intensity was inhibitory. Yan et al. (51) used an extended STIRPAT model to examine the impact of eight factors on carbon emission within the power sector of China. The results indicated that urbanization level, population, technology level, line loss, GDP per capita, power generation structure, industry structure, and energy intensity, in that order, were the major carbon emissions reasons within the Chinese power sector. Guan et al. (52) used the STIRPAT model for assessing and quantifying the nexus between carbon emissions from energy consumption and their main causes. The results of the work indicated that increasing GDP per capita, contribution to GDP of secondary industries, and urban employment promote carbon emissions. Cui et al. (53) utilized the extended STIRPAT model to investigate the socioeconomic and technological factors causing carbon emissions in China's power industry. The results revealed that it is important to reduce the low-carbon production cost, improve low-carbon production returns, and strengthen the regulation of power enterprises, while reducing the supervision cost of the government. Zhang et al. (54) utilized the STIRPAT model to investigate the impact of urbanization on carbon emissions under change of gravity center. The results revealed that the population urbanization effect was insignificant; however, population urbanization had a significantly positive spatial spillover effect. On the other hand, Li et al. (55) made use of the STIRPAT model for investigating the driving forces of carbon emissions in China for a selected period. The results showed that urbanization rate, GDP per capita population, and energy intensity had a significant positive impact on the growth of carbon emissions in China. Mensah et al. (56) utilized the STIRPAT model for examining the effect of innovation on carbon emissions in selected countries. The results revealed that an increase in GDP per capita leads to a rise in carbon emissions in the selected countries. Yang et al. (57) used the extended STIRPAT model for analyzing the main issues influencing carbon emissions, adding climatic factors based on socioeconomic factors. The results revealed that economic development, urbanization, and foreign trade were the main issues promoting carbon emissions. Noorpoor and Kudahi (58) employed a STIRPAT model to analyze the socioeconomic influencing parameters on carbon emissions. The results indicated that population size, electricity intensity, GDP per capita, and the consumption of fossil fuels for electricity generation positively influence carbon emissions.

3.4. Artificial intelligence models

A number of researchers have employed artificial intelligence (AI) techniques for carbon emissions modeling. Mustapa et al. (59) utilized a non-linear autoregressive exogenous neural network model to investigate the connection between energy usability, economic indicators, and carbon emissions in Asian countries. The study revealed that coal consumption highly affected CO_2 emissions in the countries studied. Mardani et al. (60) as well as Wen and Yuan (61) developed a multistage model for predicting carbon dioxide emissions using machine learning techniques including particle swarm optimization and neural networks. Ahmadi et al. (62) employed hybrid stochastic modeling using the Bayesian approach and scenario analysis for forecasting long-term energy demand and greenhouse gas reduction potential. The results revealed that in the long run, carbon emissions will reduce if there is an uptake of energy saving solutions. Hassouna and Al-Sahili (63) conducted a research study with the aim of developing prediction models for quantifying the energy and environmental implications of electric vehicles in Palestine. The research showed that significant amounts of greenhouse gas emissions could be reduced by introduction of electric vehicles. Ghalandari et al. (64) used the group method of data handling and multilayer perceptron methods for estimating carbon dioxide emissions in selected European countries. The results revealed that the multilayer perceptron method is preferred due to its lower average relative error value. Ferreira et al. (65) employed a multilayered artificial neural network (ANN) for evaluating costs and carbon emissions of the electrical infrastructure in data centers. The work proposed a model that can forecast consumption based on the energy consumption history of the data center. Jashnani et al. (66) employed an ANN approach for determining carbon emissions based on shares of various energy sources used as primary energy supply and GDP as an economic indicator. After being applied to five countries, the results of the model showed that the ANN model was accurate enough for predicting carbon emissions. Xu et al. (67) utilized dynamic non-linear artificial neural networks for determining China's carbon emissions peak. The results of the work revealed that China's peak carbon emissions will occur in 2029, 2031, or 2035 under low-growth, benchmark moderate-growth, and high-growth scenarios. Gong et al. (68) utilized a data-based clustering algorithm for examining the connection between GDP, consumption of energy, and emissions of carbon in China. The results of the work indicated that the model is a viable tool for analyzing the real-world effects of decarbonization policies. Huang et al. (69) utilized the Elman neural network with the firefly algorithm for forecasting China's carbon emissions. The results of the work indicated that the firefly algorithm optimized Elman neural network performs better than the Back Propagation Neural Network and Elman neural network for carbon emissions prediction. Similarly, Acheampong and Boateng (70) applied ANN for forecasting carbon emissions in China, Australia, USA, Brazil, and India. The results of the work indicated that the ANN models developed have been validated and deemed reliable to predict the growth of carbon emission intensity for China, Australia, USA, Brazil, and India with negligible forecasting errors. Wang and Li (71) utilized a PSO algorithm-based gray Verhulst model for modeling the non-linear connection between economic growth and carbon emissions. The results indicated that the relationship between carbon emissions and economic growth was of the form of an inverted U-shape with emissions being in a rapid growth stage on the curve's left. Zhao and Niu (72) applied a wavelet neural network prediction model to predict the carbon emissions of China's power generation industry. The results indicated that standard coal consumption, population, thermal power specific gravity, and per capita GDP are the key factors affecting the carbon emissions from the power generation industry. Özceylan (73) applied particle swarm optimization and artificial bee colony models to estimate the carbon emissions in Turkey based on socioeconomic indicators. The results proposed models that were useful for forecasting carbon emissions to year 2030 under different scenarios. Marjanović et al. (74) used the extreme learning machine to predict GDP based on carbon emissions. The results indicated that the extreme learning machine can be effectively utilized in GDP forecasting.

3.5. Simultaneous equation models

Simultaneous equation modeling has been used widely in carbon emissions modeling. Fu et al. (75) utilized simultaneous-equation models and Sobel tests to investigate the nexus between environmental performance and international sanctions, thereby showing that the intermediate effect on GDP between environmental performance and international sanctions was mainly negative. Khan et al. (76) utilized simultaneous equations to investigate the connection between natural resources and tourism in energy-growth-CO_2 emission nexus. The study revealed a bidirectional causality relationship between income and tourism with natural resources contributing to energy use, tourism development, and carbon emissions in the countries studied. Ahmad et al. (77) used a simultaneous equation modeling approach for investigating the connection between innovation, energy, environment, and growth in selected countries. The results revealed that a two-way causality exists between energy consumption per capita and GDP per capita, signaling that pollution was below the threshold of the maximum, while fossil fuel consumption was the primary source of CO_2 emissions. Arminen and Menegaki (78) utilized simultaneous equation modeling to examine the causal relationships between consumption of energy, carbon emissions, and economic growth in countries of various social strata. The results indicated that GDP and energy consumption expressed bidirectional causal relationship; however, there was no support for the environmental Kuznets curve. Chaabouni (79) used artificial neural network models and dynamic simultaneous-equation panel data for investigating the carbon emissions, energy consumption, and economic growth in East Asian countries. The results revealed bidirectional causality between consumption of energy and growth of the economy, bidirectional causality between economic growth and carbon emissions, and unidirectional causality between carbon emissions and energy consumption.

3.6. Regression models

Some researchers have utilized regression models for carbon emission modeling. González-Sánchez and Martín-Ortega (80) utilized multiple linear regression models for examining the determinants of greenhouse gas emissions. The research indicated that GDP and final energy intensity are the main drivers for greenhouse gas emissions reduction in Europe. Similarly, Yaya (81) employed mean-based regression models based on quantile regression for investigating the factors that drive pollution in high- and low-pollution countries. The results showed that energy consumption and financial development cause a rise in emissions and this effect is larger in countries with lower levels of pollution. Koengkan et al. (82) utilized the quantile regression econometric technique for assessing the renewable energy consumption effect on air pollution reduction. The results indicated that fossil fuel consumption impacts mortality rate positively and economic growth negatively. Ike et al. (83) utilized the method of moments quantile regression methodology to examine the oil production effect on carbon emissions in selected countries that produce oil. The results showed that there was an inverted U-shape relationship between economic growth and CO_2 emissions with a positive democracy effect across all the quantiles. Ardakani and Seyedaliakbar (84) employed multivariate linear regression modeling to examine how CO_2 emissions are affected by energy consumption and GDP in selected oil-abundant countries. It was discovered that the implementation of appropriate economic and social policies would decrease the carbon emissions of these countries while improving economic growth. Chen et al. (85) employed the panel smooth transition regression model to examine the effects of government environmental regulation and changes in industrial structure on carbon emissions. The results showed non-linear effects of environmental regulation and industrial structure on carbon emissions. Tavakoli (86) employed single and multiple linear regression models for evaluating four driving forces of greenhouse gas emissions. The results revealed that factors such as carbon intensity, energy intensity, and population are the critical factors leading to more greenhouse gas emissions. Armeanu et al. (87) utilized regression for investigating the link between environmental pollution and economic growth in European countries. The results revealed that there was no causal link between economic growth and primary energy consumption. Tariq et al. (88) used the multiple linear regression model for evaluating the relationship between carbon emissions and economic variables such as energy use, urban population, gross capital formation, and GDP at market prices. The results indicated that the most effective predictor for carbon emissions is energy use. Zaidi et al. (89) used inverse function regression to study the link among consumption of energy, growth of the economy, and CO_2 emissions. The results revealed that energy consumption and GDP affect carbon emissions, and higher energy consumption and lower GDP could give rise to water and air pollution environmental problems. Aydin (90) utilized multiple linear regression analysis for analyzing the main indicators affecting energy-related carbon emissions in Turkey. The results indicated that country population is a highly significant variable for explaining energy-related carbon emissions in Turkey.

3.7. Data envelopment analysis models

Some researchers have used data envelopment analysis (DEA) models for carbon emission modeling. Yu et al. (91) utilized a DEA model for analyzing the contribution rate of economic, energy, and population effects on carbon emissions in China. The results showed that energy consumption per unit of GDP and per capita GDP are the key factors that lead to changes in carbon emissions. Lu et al. (92) utilized a dynamic slack-based DEA model to examine the environmental energy efficiency of high-income economies. The results indicated that highly energy-efficient economies may consume a large amount of energy and are poor at carbon emissions reduction. Cucchiella et al. (93) used DEA models for identifying competitive European Union member states and proposing novel energy consumption and country greenhouse gas limits allocations. The results revealed that though the initial allocations were inefficient, applying the modeled reallocation would lead to potential increases in emission and energy consumption. Meng et al. (94) utilized a DEA model for evaluating the low-carbon economy efficiency analysis of provinces of China. The results revealed that among other findings, the efficiencies of most provinces had rising trends, implying positive contribution of previous efficiency policies. Vlontzos et al. (95) used a DEA model for environmental Kuznets curve testing in the European agricultural sector. The results revealed that each country's sustainable production practices adoption potential has no connection with its economic development. Olanrewaju and Mbohwa (96) utilized Index Decomposition Analysis (IDA), ANN, and DEA models for assessing greenhouse gas emissions reduction. The results showed how the three different models can be integrated into one system and demonstrated how much percentage of an industry's carbon emissions can be reduced. Zeng et al. (97) employed the zero-sum gains DEA model for examining the non-fossil energy consumption and carbon emission reduction allocative efficiency. The results provided an allocation scheme with good efficiency for all cities and provinces of China through iterative calculations.

3.8. Other modeling approaches

Leitão and Balogh (98) conducted a study to investigate the agricultural, intraindustry trade, and energy use impact on environmental pollution in European countries. The results showed that international trade affects the environment negatively, while intraindustry trade is more favorable. Leitão and Lorente (99) utilized the fully modified least squares, dynamic least squares, and generalized moments system estimator to investigate the relationship between renewable energy, economic growth, tourism arrivals, carbon emissions, and trade openness in the European Union. The results indicated that economic growth has a positive effect on carbon dioxide emissions and tourism arrivals have a negative correlation with carbon dioxide emissions. Chontanawat (100) aimed to study the connection between economic growth, energy consumption, and CO_2 emissions of Asian countries. The results revealed that there was unidirectional causality between economic growth and energy consumption in the Asian countries and adopting policies that would conserve energy would not constrain growth of the Asian countries. Magazzino et al. (101) evaluated the relationship between greenhouse gas emissions, GDP, and municipal waste generation in Switzerland, employing stationarity and causality tests as well as machine learning models. The study revealed that municipal solid waste generation and GDP had a bidirectional causal relationship, with composting and recycling mitigating greenhouse gas emissions. Ghanbari and Mansouri Daneshvar (102) employed correlation test and clustering analysis models for investigating greenhouse gas emissions in Central Asia and Middle East countries. The study revealed that certain countries within the region such as Iran, Saudi Arabia, and Turkey highly contributed to greenhouse gas emissions within the region. Olanrewaju et al. (103) utilized the panel data model for investigating the determinants of renewable energy consumption in Africa, discovering that there is a negative relationship between renewable energy consumption and energy intensity in Africa. Falconi et al. (104) utilized a country-based econometric simulation model for evaluating the relationship among carbon emissions, energy efficiency, GDP, and energy consumption. The research showed how the toxic assets concept can be related to toxic income (the income level that would generate levels of carbon emission which make keeping climate change under control difficult). Cary (105) compared an environmental Kuznets curve model with a model containing only a linear GDP per capita term and discovered that by utilizing a subsector level modeling approach, evidence for the environmental Kuznets curve hypothesis is non-existent. Hsiao et al. (106) employed a stochastic frontier analysis (SFA) model for measuring disaggregate input efficiency and total-factor energy efficiency for selected countries. The results indicated that the average energy use efficiency scores exhibited an upward trend.

Ahmadi et al. (107) employed connectionist models with Least Square Support Vector Machine for predicting the amount of carbon emissions in selected Latin American countries. The results indicated that apart from Venezuela, all other selected countries had invested in renewable energy research and development activities. Omrani et al. (108) used weighted goal programming models for allocating the optimum workforce among four sectors, services, agriculture, transportation, and industry, based on indicators such as GDP, electricity, and energy consumption as well as greenhouse gas emissions. The results indicated that the best individuals for making optimized decisions and macroeconomic and regional planning are policy makers and the government. Luo et al. (109) used structural decomposition analysis based on an input–output model for analyzing the driving forces of carbon emissions. The results indicated that clean energy sector carbon emissions were lesser compared to thermal power emissions and carbon emission increments were mainly caused by consumption volume. Bai et al. (110) utilized an optimization model for handling economic, energy, environmental, and social sustainable development problems. The result of the work was the proposal of an optimization model for resource allocation and planning future labor. Kumar and Muhuri (111) developed a GDP prediction model based on carbon emissions data. The work proposed a model that can predict per capita GDP of different developing or developed countries using their carbon emissions data. Jia et al.

(112) proposed a multiobjective optimization model for labor allocation across economic sectors and simultaneously satisfying economy, environment, energy, and society. The results showed that the model is quite efficient in the uncertain environment and provides a reliable decision tool than deterministic models for integrated multiobjective sustainable development problems. Wang et al. (113) utilized an improved gray wolf optimizer support vector machine model for predicting carbon emissions. Based on the results, the authors proposed relevant carbon emissions policies for controlling emissions from the source. Lai et al. (114) as well as Woodard et al. (115) employed improved Kaya models for examining the relationship and trends among energy consumption, carbon emission, carbon emission intensity, and GDP growth rate of the construction industry of China. The results revealed that the construction industry carbon emissions are mainly affected by the growth of GDP, while energy consumption was the major reason for increased CO_2 emissions. Sutthichaimethee and Ariyasajjakorn (116) employed the autoregressive integrated moving average with explanatory variable forecasting model for predicting carbon dioxide emissions in Thailand's industry sectors. The results of the work revealed that Thailand will have higher carbon emissions in 15 and 30°year periods. Meng and Huang (117) made use of spatial Durbin models for analyzing the connection between growing economies and carbon emissions in cities of China. The results indicated that policy makers need to judiciously take regional differences and intrinsic spatial interactions between factors into consideration when formulating policies for carbon reduction.

Dogan and Aslan (118) employed heterogeneous panel estimation techniques with cross-sectional dependence for analyzing the connection between real income, carbon emissions, tourism, and energy consumption for selected European countries. The results revealed that tourism to carbon emissions had one-way causality, while carbon emissions and energy consumption as well as real income and carbon emissions had two-way causality. Jayaraman et al. (119) employed a weighted goal programming model considering GDP, greenhouse gas emissions, and electricity consumption to obtain the optimum labor allocation across various sectors of the economy. The results provided empirical evidence and enabled policy analysts and decision makers to have a better understanding while developing optimal strategies for simultaneously satisfying labor development, energy demand, energy growth, and greenhouse gas emissions reduction for increased sustainability. Zhang et al. (120) used non-linear programming models for analyzing the likely effects of Chinese carbon trading. The results indicated that carbon trading, from a theory-based view, raised the shadow price of carbon and had a non-linear correlation with carbon emissions that is negative. Khan et al. (121) employed a panel generalized method of moments while examining the connection between energy-resource depletion, health resources, environmental Kuznets curve, and climate change under the financial constraint environment of selected developed countries. The results confirmed the existence of the environmental Kuznets curve hypothesis in the energy-resource depletion model, within the countries. Song et al. (122) employed a fuzzy chance-constrained goal programming model for optimizing economy, energy, and environment. The results of the study on Shandong province in China revealed that the model can reflect the inherent relationship and evolution law of economy, energy, and environment and provide effective decision-making support for optimizing economy, energy, and environment. Pao et al. (123) applied the Lotka-Volterra model for investigating the various interactions among environment, energy, and economy in the United States. The results revealed a pure competition among emissions and GDP, and the model provides a useful multivariate framework to predict outcomes concerning those interactions.

Figure 2 is a diagrammatic representation of the various models used for analyzing and exploring the effect of greenhouse gas emissions on the global climate.

Figure 3 shows the trend of carbon emissions models from 2015 to 2020. From Figure 3, there is a rising trend in the

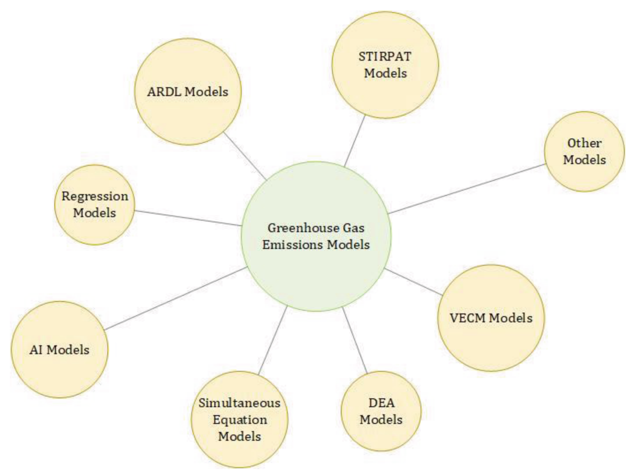

FIGURE 2 | Greenhouse gas emissions models.

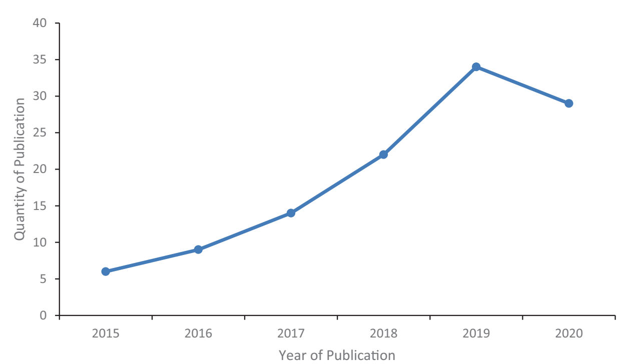

FIGURE 3 | Trend of carbon emissions models from 2015 to 2020.

TABLE 1 | Most predominant journal for publication.

Journal	Articles	% of total
Journal of cleaner production	15	13.16
Environmental science and pollution research	14	12.28
Science of the total environment	6	5.26
Sustainability	6	5.26
Energies	6	5.26
Renewable and sustainable energy reviews	6	5.26
International journal of energy economics and policy	3	2.63
Energy strategy reviews	3	2.63
Energy	3	2.63
Applied energy	3	2.63
Others (44)	49	42.98
Total	**114**	**100**

research interest in carbon emissions modeling. This can be explained by the increased incidence of natural disasters occurring as a result of the global warming phenomenon due to greenhouse gas emissions from human activities like deforestation and fossil fuels use.

Table 1 shows the most predominant journal for publication of carbon emissions models. From Table 1, the most predominant journal for publication of carbon emissions analysis models is Journal of Cleaner Production with a total percentage of reviewed publications of 13.16%.

4. Conclusion

Greenhouse gas emissions are a major concern across the world, especially as they are responsible for climate change and other environmental problems bedeviling human societies. Various researchers have put forward different models for carbon emissions analysis, management, and control. These models can be loosely grouped into AI, classical regression, autoregressive distributed lag, vector error correction, data envelopment analysis, simultaneous equation, and STIRPAT models. This study has considered publications that develop or utilize one or more models for carbon emissions analysis, management, and control between 2015 and 2020. The study shows that the trend in carbon emissions analysis, management, and control research is of an increasing nature. This trend can be explained by the increased incidence of natural disaster occurring due to the phenomenon of global warming caused by emissions of greenhouse gases from the activities of humans including deforestation and use of fossil fuels. Some methods for carbon emissions reduction and improved energy efficiency include carbon capture and storage as well as widespread implementation of low-carbon renewable energy systems. This implies that there needs to be a rapid change from dependence on fossil fuels for energy to low- or no-carbon energy generation methods, especially for transportation and electricity generation. Also, the implementation of various taxation/trading schemes is important for encouraging the transition to a low or no carbon economy.

Author contributions

OW-N solely developed the research work.

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