


Article

# Analyzing the Impact of GDP on CO<sub>2</sub> Emissions and Forecasting Africa's Total CO<sub>2</sub> Emissions with Non-Assumption Driven Bidirectional Long Short-Term Memory

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**Abstract:** The amount of total carbon dioxide (CO<sub>2</sub>) emissions emitted into the environment threatens both human and global ecosystems. Based on this background, this study first analyzed the relationship between gross domestic product (GDP) and CO<sub>2</sub> emissions in five West African countries covering the period of 2007–2014 based on a panel data model. Our causality analysis revealed that there exists a unidirectional causality running from GDP to CO<sub>2</sub> emissions. Second, after establishing the nexus between GDP and CO<sub>2</sub> emissions, we forecast Africa's CO<sub>2</sub> emissions with the aim of projecting future consumption levels. With the quest to achieve climate change targets, realistic and high accuracy total CO<sub>2</sub> emissions projections are key to drawing and implementing realizable environmentally-friendly energy policies. Therefore, we propose a non-assumption driven forecasting technique for long-term total CO<sub>2</sub> emissions. We implement our bidirectional long short-term memory (BiLSTM) sequential algorithm formulation for both the testing stage (2006–2014) and forecasting stage (2015–2020) on Africa's aggregated data as well as the five selected West African countries employed herein. We then propose policy recommendations based on the direction of causality between CO<sub>2</sub> emissions and GDP, and our CO<sub>2</sub> emissions projections in order to guide policymakers to implement realistic and sustainable policy targets for West Africa and Africa as a whole.

**Keywords:** CO<sub>2</sub> emissions; bidirectional long short-term memory (BiLSTM); Africa; West Africa; diversification of energy sources; climate change; forecasting

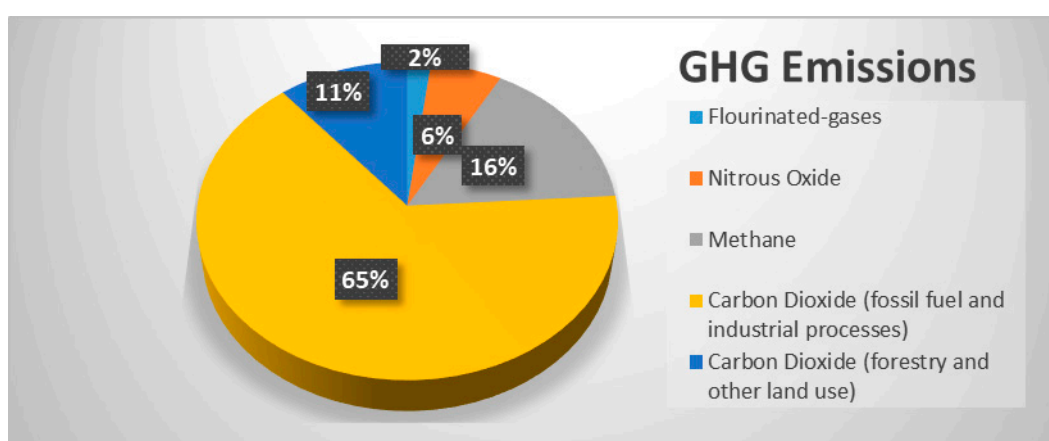
## 1. Introduction

Currently, the two topmost challenges facing humanity are sustainable economic development and environment degradation [1]. Degradation of the environment is triggered by surges in the human population, a continual increase in economic growth or per capita affluence and technological applications used in depleting of resources [2]. Environmental degradation is considered the hallmark of industrialization which is a major driver of economic development [3]. However, as the level of economic growth across many economies hinges on several factors which include the potential availability of resources, the growth of an economy may breed adverse environmental issues, over-exploitation of natural resources, degradation of wildlife habitats, and climate change [4]. With the aim of achieving sustainable economic development, many governments are in a dilemma as to whether to meet clean energy targets or combust fossils to aid in economic development [5]. Although it is arguable that combusting fossils and the depletion of natural resources for economic gain is likely

to increase the living standards of citizens [6], it is worth noting that any attempt to emit harmful toxics into the environment will endanger the living conditions of humanity and the species now and in the future [7].

In the field of energy, energy produced and consumed by conventional and exhaustible resources (fossil fuels) is considered a major threat to the environment [8]. The combustion and production of coal, oil and natural gas release harmful toxins into the environment [9]. Toxins emitted into the environment from fossil fuels have intensified renewable energy production and consumption [10]. Yet, securing the environment from emissions has come to the forefront of contemporary issues for most economies around the world [11]. The possibility of eradicating or reducing to an appreciable level emissions mainly from greenhouse gases (GHG) raises concerns about climate change and global warming [12]. As indicated by [13], global environmental change is one of the major threats facing humanity nowadays. With global environmental change issues looming mainly in the developed countries, many countries have either enacted their own policies or have partnered with other countries in implementing strategic and efficient policies for a widespread future emissions-free environment. Popular among climate change policies is the 21st Conference of Parties (COP 21) of the United Nations Framework Convention on Climate Change (UNFCCC) agreement on global climate change governance whereby each member country plans and reports its own contributions aimed at mitigating global warming [14]. The agreement proposes long-term goals to hold the increase in global average temperature below 2 degrees Celsius above pre-industrial levels and to limit the temperature increase to 1.5 degrees Celsius above pre-industrial levels [15]. With this agreement, information is relayed to member countries to help strengthen their Intended National Determined Contribution (INDC) targets and action plans by enhancing transparency of mitigation and global regular collective inventory [14]. As the agreement highlights the global response to climate change, its main drawback is that putting an end to the era of fossil fuels may lead to changes in economic development patterns, energy systems, and social governance models, thereby reshaping the competition pattern of the international economy and technology [12]. Thus, countries are likely to confront severe challenges and arduous tasks ahead.

Before the institution of the Paris Agreement, the key GHGs emitted through human activities that are considered to transmit harmful toxics into the environment are carbon dioxide (CO<sub>2</sub>), methane (CH<sub>4</sub>), nitrous oxide (N<sub>2</sub>O) and fluorinated-gases (F-gases). Amongst all the GHG emissions, total carbon dioxide emissions account for 76% of GHG emissions globally [16]. Global GHG emissions are presented in Figure 1.



**Figure 1.** Global greenhouse gas (GHG) emissions. Source: Intergovernmental Panel on Climate Change [16].

Based on Figure 1, as total carbon dioxide emissions account for 76% of global GHG emissions, the world top energy-consuming countries have tabled more sustainable policies aimed at reducing CO<sub>2</sub> emissions coupled with fostering cleaner economic growth trajectories [17].

However, to effectively control CO<sub>2</sub> emissions together with ensuring sustainable economic growth, understanding the dynamic link between CO<sub>2</sub> emissions and economic growth is key [5]. Literature exploring the relationship between CO<sub>2</sub> emissions and economic growth has concentrated on two main streams. The first stream suggests an inverted U-shaped relationship between environmental pollutants and economic growth which is known as the Environment Kuznets Curve (EKC). Recent studies on EKC includes [18,19]. Conclusions drawn from these studies reveal that there exists an inconsistent relationship between CO<sub>2</sub> emissions and economic growth. However, results from these studies are highly contingent upon regional and country-level specificities. The second stream of literature examines the relationship between energy consumption and economic growth. Some representative studies investigating this relationship are [20,21]. Conclusions on studies in this stream of literature reveal varying relational results between energy consumption and economic growth. Such a varying relationship can be attributed to the choice of datasets, model specifications, and the econometric technique involved.

Focusing on the first stream of literatures in establishing the direction of causality between GDP and CO<sub>2</sub> emissions, Ref. [22] using Granger causality test found that there exists a unidirectional causality running from GDP to CO<sub>2</sub> emissions in South Africa and a reverse relationship from CO<sub>2</sub> emissions to GDP in Brazil; however, there was no evidence of causality in the case of India and China. Also, in analyzing the dynamic links between CO<sub>2</sub> emissions and economic growth, Ref. [5] concluded that there was evidence of unidirectional causality running from economic growth to CO<sub>2</sub> emissions in China. In examining the relationship between CO<sub>2</sub> emissions and economic growth in 24 African countries using a panel autoregressive distributed lag (ARDL) approach, Ref. [23] found a long-run causality running from economic growth and CO<sub>2</sub> emissions to energy consumption. Likewise, investigating the causal relationship between economic growth and CO<sub>2</sub> emissions during the period 1980–2009 by applying the Granger causality technique for both the long and short run revealed evidence of unidirectional causality running from economic growth to CO<sub>2</sub> emissions [24]. Similarly, Ref. [25] in examining the causal relationship between CO<sub>2</sub> emissions and economic growth for a sample of 12 selected Sub-Saharan African countries, by using the Granger causality test to annual data covering the period 1971–2010, concluded that economic growth Granger-causes CO<sub>2</sub> emissions in the short-run in Benin, Democratic Republic of Congo, Ghana, Nigeria and Senegal; evidence of reverse causality running from CO<sub>2</sub> emissions to economic growth was found for Gabon, Nigeria and Togo; bi-directional causality between economic growth and CO<sub>2</sub> emissions was found in the short-run for Nigeria and in the long-run for Congo and Gabon.

For the nexus between CO<sub>2</sub> emissions and economic growth, we analyze this relationship by selecting five (5) West African countries, namely Ghana, Nigeria, Burkina Faso, Senegal and Benin. We select these countries based on data consistency and uniformity. As we are aware of the existence of extensive literature on the causal relationship between CO<sub>2</sub> emissions and economic growth, this study goes further to formulate an algorithm to forecast Africa's CO<sub>2</sub> emissions which are lacking in literature as of now. As there are numerous prediction tools (univariate and multivariate forecasting tools) for carbon emissions and its applications, we use a univariate forecasting technique because we aim to avoid the challenge of measuring and determining the influence of causal variables on our main dependent variables. As indicated by [26], univariate forecasting has existed for decades. To mention a few works that have employed univariate forecasting, Ref. [26] formulated an algorithm to forecast the U.S. sectoral energy demand and drew their conclusions based on the predictive accuracy of the algorithm for the commercial sector, industrial sector, residential sector and transportation sector. Also, Hu [27] employed used a neural-network-based grey residual modification model for energy demand forecasting and concluded on the predictive accuracy of their model formulation. Furthermore, Abdel-Aal [28] employed a neural and abductive network for monthly energy demand forecasting and concluded that using a single next-month forecaster is highly accurate. For our study to be more distinct from previous studies in Africa mostly analyzing the causal relationship, we formulate our own algorithm based on the recurrent neural network (RNN)-based bidirectional long short-term

memory (BiLSTM). To overcome the limitations of a regular RNN, we propose a bidirectional recurrent neural network (BiRNN) that can be trained using all available input information in the past and future of a specific time frame. We use BiLSTMs because it is an extension of traditional LSTMs that can improve an algorithm's performance on sequence classification problems. The predictive outcome of our algorithm formulation will be for our testing stage and forecasting stage. Ideally, it would have been viable to test our algorithm formulation test output against country-case total CO<sub>2</sub> emission projected values. Rather, previous International Energy Outlook (IEO) editions could not capture country-case total CO<sub>2</sub> emissions data on each of our selected West African countries. Therefore, we make an assumption that if our BiLSTM test output year-over-year (YoY) errors outperform previous IEO editions' aggregated projections for Africa, our algorithm is likely to outperform country-case projections. Therefore, for the country-case study, we present our test output against the observed values and check its performance. We set a threshold that if our accuracy for Mean Absolute Percentage Error (MAPE) is above 90%, we will go on to make long-term future projections to the year 2020. Long-term as used herein represent a timeline of five years or more [29].

In a nutshell, as we prefer that this research ends by proposing policy measures to mitigate CO<sub>2</sub> emissions to an appreciable level in the selected West African countries employed herein, we first present on existing environmental tax models that aim to reinforce cleaner energy targets. First, the existence of fiscal policy instruments (environmental tax) asserts that taxes should be leveraged on activities that cause harm to the environment. Based on environmental tax models, African countries have been urged to start national carbon tax systems in readiness for carbon taxing regimes. However, in an extremely coal-reliant economy, the proposed carbon tax policies are likely to have significant financial consequences for industries that are either unprepared to implement the carbon tax or unable to mitigate its effects. Based on this background, we formulate our own algorithm for estimating future CO<sub>2</sub> emission levels which will help policymakers to propose realistic and sustainable emission-free policies in Africa particularly, West Africa. Also, the use of RNN to forecast CO<sub>2</sub> emissions in Africa is lacking in literature, and our study will encourage researchers to replicate our algorithm formulation or propose a different algorithm for future CO<sub>2</sub> emission comparisons. Finally, although Africa is not a high emitter of GHG emissions, this study aims to contribute its quota to realizing climate change targets for the ultimate goal of a sustainable emissions-free environment in Africa.

## 2. Materials and Methods

### 2.1. Data Source for Panel Analysis

First, we focus on the panel data evidence for country-specific CO<sub>2</sub> emissions data from selected West African countries (Ghana, Nigeria, Burkina Faso, Senegal and Benin) all in thousands of tons. However, the data available is not uniform because some countries have data up to 2016 while the last updated data for other countries was 2014. For data uniformity, we chose the years spanning from 2007–2014. The representation of all causal variables and CO<sub>2</sub> emissions used in our panel data is converted into their natural logarithm forms and listed Table 1.

**Table 1.** Data display of all variables in the panel.

Variables	Definition	Data Source	Unit
CO <sub>2</sub>	Carbon dioxide emissions	WIND [30]	1000 tons
GDPC	Gross domestic product per capita	WDI [31]	Constant 2010 US\$
LF	Labor force	WDI [31]	Total Labor force
GFCF	Gross fixed capital formation	WDI [31]	Percentage (%) of GDP

Notes: Country-case data was obtained from the WIND data portal; GDPC, LF and GFCF data is obtained from the World Development Indicators.



Although CO<sub>2</sub> emissions from the African continent and its countries account for an insignificant portion of global CO<sub>2</sub> emissions [32], recent trends show that there is a continual rise in CO<sub>2</sub> emissions for Africa and the selected West African countries herein [33]. We use CO<sub>2</sub> emissions as the dependent variable because of its upsurge; gross domestic product per capita (GDPC) is employed because it is selected to represent the growth of an economy. Although literature shows that international trade is the main drive of CO<sub>2</sub> emission [34,35], this study sets labor force [36] and gross fixed capital formation [37] as control variables by selecting labor force and gross fixed capital formulation from the Cobb–Douglas production function [38]. Labor force and gross fixed capital formation are selected as control variables because energy is known to influence productivity [39]. On a macroeconomic scale, the relationship between energy consumption, capital, labor force, and economic growth is described by a production function. The maximization of this production function determines a sequence of optimal savings, investment and consumption decisions. Explaining further, carbon dioxide emissions are obtained from the amount of fossil fuels consumed. Therefore, CO<sub>2</sub> emissions and non-renewable energy consumption have a direct impact on a macroeconomic perspective. Specifically, labor force and gross capital formulation are likely to influence CO<sub>2</sub> emissions on a macroeconomic scale if more non-renewables are consumed. On the economic relationship between labor force and CO<sub>2</sub> emissions, as Africa’s technologies for renewable energy are limited [40], it is fair to point out that the use of fossil fuels is dominant. Therefore, an increase in the labor force will drive an upsurge in the consumption of fossil fuels thereby causing a corresponding increase in CO<sub>2</sub> emissions. Moreover, the assets used in the production of energy-related resources requires capital. Furthermore, as the carbon footprint is the amount of greenhouse gases—primarily carbon dioxide—released into the atmosphere by a particular human activity, an increase in human activity that requires a greater labor force connotes a corresponding increase in CO<sub>2</sub> emissions if there is a limited or untapped renewable energy technology. Economically, ignoring the relationship of carbon footprint and gross fixed capital formation, labor force and CO<sub>2</sub> emissions is a pretty big oversight. We present the data for all our variables used for the panel in Figure 2.

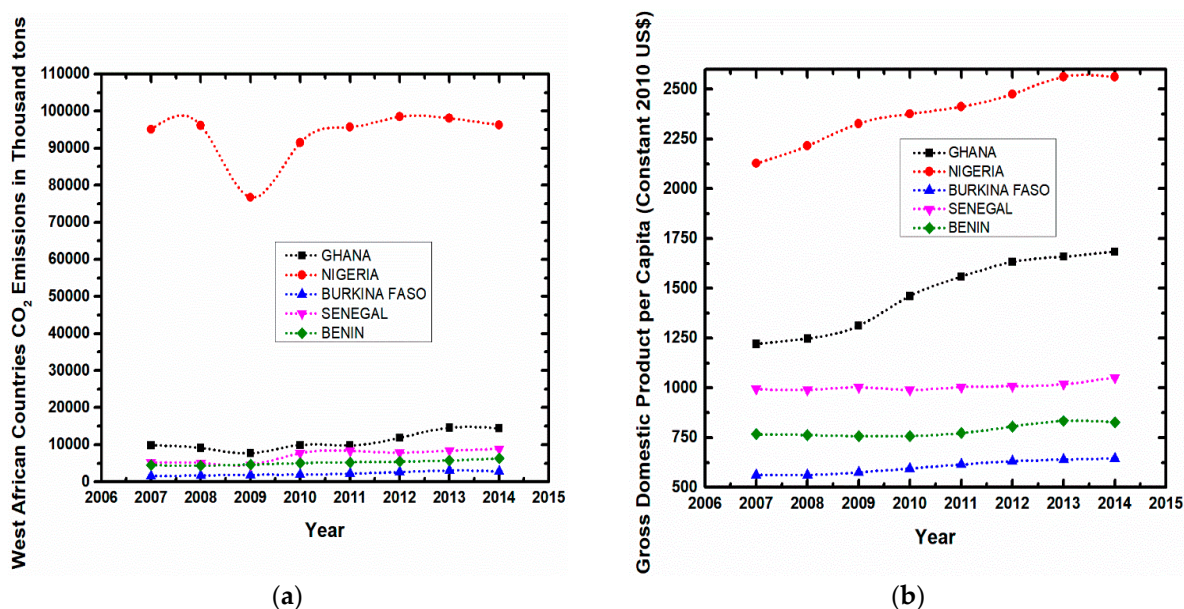


Figure 2. Cont.

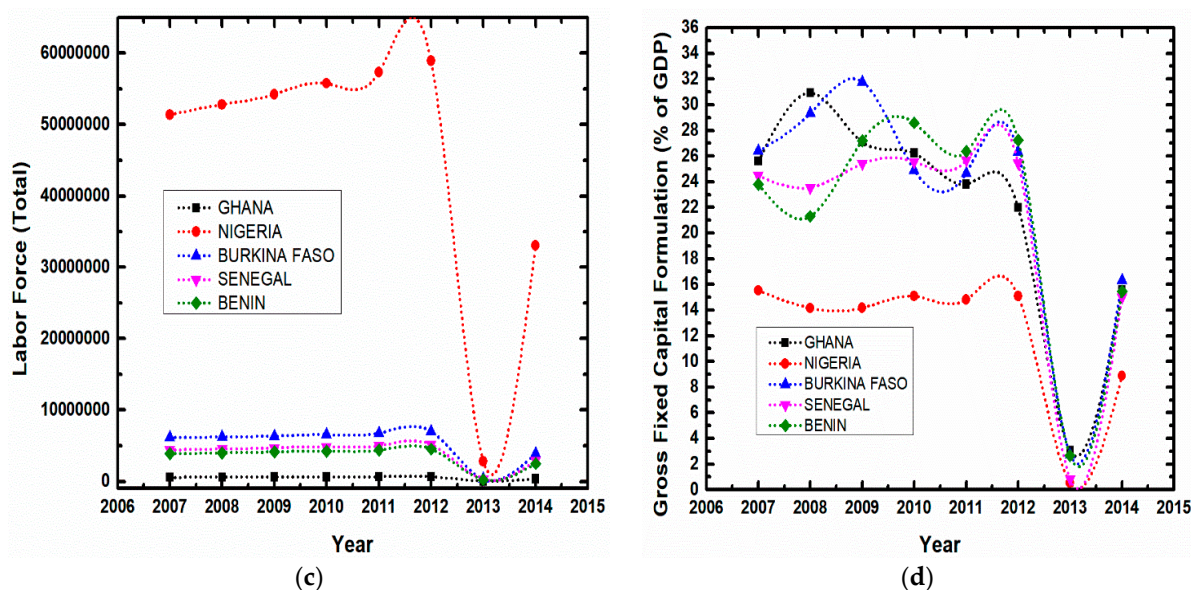


Figure 2. Panel data variables for CO<sub>2</sub> emissions (a), GDPC (b), LF (c) and GFCF (d).

### 2.2. Panel Economic Model Method

In order to start with the appropriate methods for our unit root test, we employ the Pesaran cross-sectional dependency test [41]. We develop our panel model as:

$$z_{it} = \alpha_i + \beta_{it}y_{it} + \mu_{it} \tag{1}$$

where  $i = 1, 2, \dots, N$  is the subscript of each West African country is employed herein;  $t = 1, 2, \dots, T$  represents our study time dimension;  $\beta_{it}$  represents a parameter vector for the evaluation of our causal variables;  $y_{it}$  represents each of the causal variables;  $\alpha_i$  indicates the constant parameters and  $\mu_{it}$  is our error term. We define both our null and alternative hypothesis as:

$$H_0 : \gamma_{ij} = \gamma_{ji} = cor(\mu_{it}, \mu_{jt}) = 0 \text{ for } i \neq j \tag{2}$$

$$H_a : \gamma_{ij} = \gamma_{ji} \neq 0 \text{ for } i \neq j \tag{3}$$

Mathematically, we formulate  $\gamma_{ij} = \gamma_{ji}$  as:

$$\frac{\sum_{t=1}^T \mu_{it}\mu_{jt}}{\left(\sum_{t=1}^T \mu_{it}^2\right)^{\frac{1}{2}} \left(\sum_{t=1}^T \mu_{jt}^2\right)^{\frac{1}{2}}} \tag{4}$$

For our test sample, we employ [41] an improvement on [42] the Lagrange multiplier test (LM) since it is suitable for this current study. Pesaran [41] formulated his version of the LM test as:

$$\sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \tau_{ij} \rightarrow N(0,1) \tag{5}$$

where  $\tau_{ij}$  represents the residual coefficients of our panel model.

After the Perasan cross-sectional dependency test is achieved, we first employ the Im, Pesaran and Shin (IPS) test developed by [43] which allows for heterogeneous autoregressive coefficients. We formulate our mathematical model as:

$$\Delta z_{it} = \gamma_i z_{it-1} + \delta_i Y_{it} + \varepsilon_{it} \tag{6}$$

where  $Y_{it}$  represents our predictor variables comprising individual time trend; autoregressive coefficients is represented by  $\gamma_i$ ; and  $\varepsilon_{it}$  represent the stationary stochastic error terms. Since there may be evidence of autocorrelation in Equation (6), we use the Levin et al. [44] exploration of high order differential delay terms formulated as:

$$\Delta z_{it} = \gamma_i z_{it-1} + \sum_{j=1}^{\gamma_i} \phi_{ij} \Delta z_{it-1} + \delta_i Y_{it} + \varepsilon_{it} \quad (7)$$

where the number of lags in the Augmented Dickey–Fuller (ADF) regression is represented by  $\gamma_i$ . We propose our null hypothesis to be a case where there exists a unit root in each series of our panel data sets whereas an alternative hypothesis supposes that at least one individual series in the panel data is stationary.

After our variable sequence is confirmed to be stable, the Pedroni [45] heterogeneous panel cointegration test is employed. The regression equation becomes:

$$z_{it} = \alpha_i + \delta_i + \beta_{1i} Y_{1i,t} + \beta_{2i} Y_{2i,t} + \beta_{3i} Y_{3i,t} + \varepsilon_{it} \quad (8)$$

where  $\alpha_i$  and  $\delta_i$  represents each country's deterministic trends;  $\varepsilon_{it}$  represents the residuals as a result of deviations from the long-run relationships. We propose our null and alternative hypothesis as there is no and there is co-integration between our variables in the long-run. Cointegration analysis comprises (panel and group) as proposed by [45]. The panel test established on the Within-Dimensions form comprises Panel v-Statistic, Panel rho-Statistic, Panel PP-Statistic and Panel ADF-Statistic by pooling dissimilar countries autoregressive coefficients for unit root investigations on estimated residuals. The group test also established on the between-Dimensions form comprises Group rho-Statistic, Group PP-Statistic and Group ADF-Statistic. The group test is performed to check individual autoregressive coefficients associated with the unit root investigations of the residual for each country in our panel [46,47].

Cointegration between two data sequence reveals the existence of Granger Causal relationships between the variables [48]. We utilize the Granger causality test [49] to analyze the influence of one data sequence on another. We define our null hypothesis as a particular data sequence does not Granger-cause another data sequence. In analyzing the causal relationships amongst our variables, the mathematical formulation is presented as:

$$z_t = \alpha_0 + \sum_{i=1}^r \alpha_i z_{t-i} + \sum_{i=1}^r \beta_i y_{t-i} + \varepsilon_t \quad (9)$$

$$y_t = \alpha_0 + \sum_{j=1}^x \alpha_j z_{t-j} + \sum_{j=1}^x \beta_j y_{t-j} + \varepsilon_t \quad (10)$$

### 2.3. Data Source and Conversion for Training, Testing and Forecasting Stage

Here, we focus on univariate forecasting of the aggregated data for Africa and the selected West African countries used in this study spanning from 1980–2014. The data time dimension spans from 1980 to 2014 because we are not able to obtain consistent data for both our country-case scenarios and Africa. Therefore, in terms of uniformity, this time dimension is suitable for this study.

We employ our univariate forecasting based on RNN-based BiLSTM for training, testing and forecasting. For the aggregated data on Africa in million metric tons (MMT), we obtain our data from the U.S. Energy Information Administration (EIA). However, for the selected West African countries used for this study, our data were obtained from the Wind data portal in thousand tons. Therefore, for data consistency, all data units in 1000 tons is converted to MMT using International Energy Agency (IEA) unit converter where 1000 tons = 0.00090718474 MMT [50]. Our training data set covered the period from 1980 to 2005. After training, we test our model output for the period of 2006 to 2014 and



make future projections from 2015 to 2020. The BiLSTM testing stage output for Africa is compared with the EIA's IEO 2010 [51], IEO2011 [52], and IEO2013 [53] projections for total CO<sub>2</sub> emissions. We compare our testing stage output with past IEO editions because it captures forecast projections for all the continents in the world. Also, IEOs are able to capture the intricate patterns in the world's energy market, technological advancements and well as demographic factors into their model [26]. For our testing stage, IEO2010 presents projections for the year 2005 and 2006; IEO2013 presents projections for 2009 and 2010; and IEO2011 presents projections for 2011 and 2012. Past editions of the IEO could not capture Africa's total CO<sub>2</sub> emissions for the year 2008, 2013 and 2014. Therefore, a comparison of these years is not made. Before presenting on our sequential algorithm formulation, we first show a pictorial evidence on total CO<sub>2</sub> emissions in Africa and the selected West African countries from 1980–2014 in Figure 3.

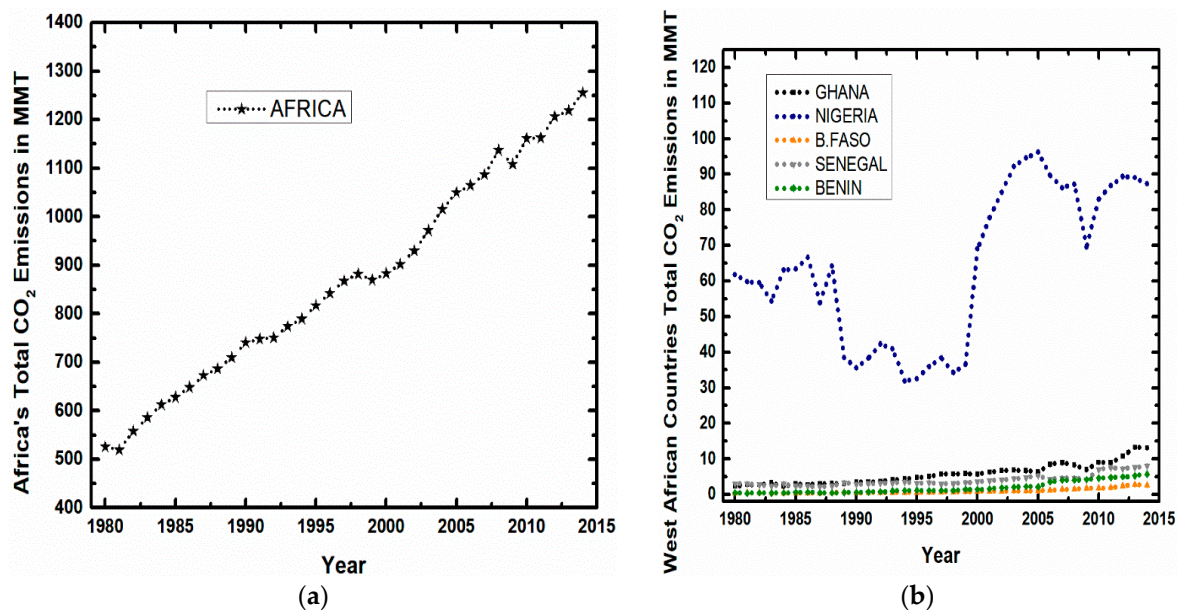


Figure 3. Total CO<sub>2</sub> emissions in Africa (a) and the selected West African countries (b).

From Figure 3, it is evident that the total amount of CO<sub>2</sub> emissions in Africa increases with respect to time. However, for the selected West African countries, the total amount of CO<sub>2</sub> emitted into the environment has experienced steady growth except for Nigeria whose CO<sub>2</sub> emissions fluctuate with respect to time. Thus, we formulate a BiLSTM algorithm that is capable of mimicking the intricate patterns in the data for a better forecasting output.

#### 2.4. Bidirectional Long Short-Term Memory (BiLSTM) Algorithm Formulation Processes

In the elimination of the restraining factors of extant approaches to non-structural forecasting, we developed our sequential algorithm using a deep-learning approach, with long short-term memory (LSTM) cells. The analysis of times series data in addition to previous relationships becomes complex. As time steps increase, these relationships become difficult to capture and reflect. Meanwhile, LSTM networks, which evolved from a traditional recurrent neural network model can consider previous relationships as time progressed. In this work, we focused on improving the robustness of predictions with a BiLSTM network. Here, we present a traditional LSTM network in Figure 4.



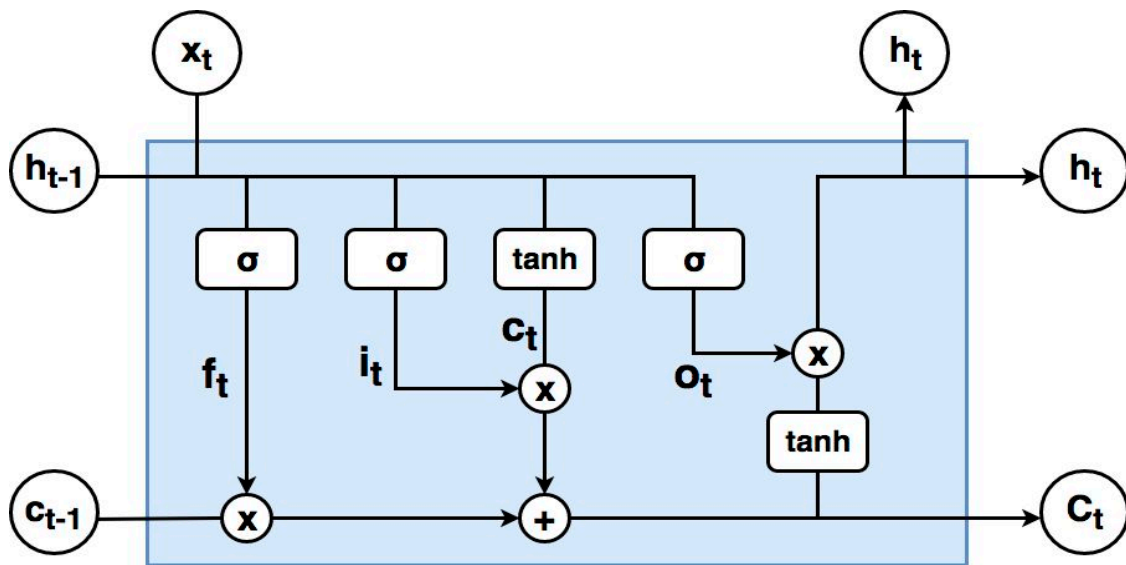


Figure 4. The author formulated long short-term memory (LSTM) diagram.

In each LSTM cell of our BiLSTM, there exists the sigmoid layer ( $\sigma$ ), tanh layer and pointwise operations of summation and multiplication. In the diagram above, the output from the forget gate layer ( $f_t$ ) is formulated as:

$$f_t = \sigma(w_f \times [h_{t-1}, x_t] + b_f) \quad (11)$$

where  $w_f$  is the hidden weight in the forget gate layer;  $h_{t-1}$  is the hidden vectors at the previous time;  $x_t$  is the variable input at a time; and  $b_f$  is the forget gate biased vector.

The output from the input layer ( $i_t$ ) is formulated as:

$$i_t = \sigma(w_i \times [h_{t-1}, x_t] + b_i) \quad (12)$$

where  $w_i$  is the hidden weight in the input gate layer and  $b_i$  is the input gate biased vector.

The output from the tanh layer ( $c_t$ ) is formulated as:

$$c_t = \tanh(w_c \times [h_{t-1}, x_t] + b_c) \quad (13)$$

where  $w_c$  is the hidden weight from the tanh layer output and  $b_c$  is the tanh layer output biased vector.

The output from the current cell state of the cell ( $C_t$ ) is formulated as:

$$C_t = f_t \times C_{t-1} + i_t \times c_t \quad (14)$$

where  $C_{t-1}$  is the cell state of the previous cell.

Our output gate layer ( $O_t$ ) is formulated as:

$$O_t = \sigma(w_o \times [h_{t-1}, x_t] + b_o) \quad (15)$$

where  $w_o$  is the hidden weight in the output gate layer and  $b_o$  is the output gate layer biased vector.

Finally, our hidden vectors ( $h_t$ ) is formulated as:

$$h_t = O_t \times \tanh(C_t) \quad (16)$$

Traditional LSTM, are limited in the sense that, at any particular node, they can have access to only the past information and hence the output can only be generated based on what the network has seen (obviously the learned information as well). Our BiLSTM has two networks, one accesses information in the forward direction and another accesses in the reverse direction. We create two independent LSTM networks and put them together. We then feed the input sequence in normal time order for one network, and in reverse time order for another. This enables our model to have access to past and future information during its training and prediction phases; hence, the output is generated from both the past and future contexts. This gives our BiLSTM-based network information persistence and increased performance.

Our sequential algorithm framework which comprises the train and test dataset is fed into the architecture as input. The time series data is then converted by our input module to a stationary form. Similar to other neural network techniques, BiLSTM cells keep data within the network activation function. Setting our BiLSTM network as a hyperbolic tangent (tanh), we specify a minimum  $[-1]$  and maximum  $[1]$  range for our time series data in order to perform a normalization of the inputs which further guarantees stable convergence of weight and biases. As in [26], we formulate this as:

$$x_s = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{17}$$

In learning the data trends and volatilities, our network utilizes a stack of LSTMs. Stacking our LSTMs' hidden layers propels our model to conform to deep learning techniques [54]. In our network, we use a concatenation method to merge the forward and backward outputs, and their combination is passed on to the next and to the last output layer. Furthermore, rectified linear unit (ReLU) is set as our model's activation function in order to decide whether a neuron should be activated or not [55]. Again dropout blocks are added to our model to check each neurons' weighted contributions to the general network model [56]. We implement a dropout percentage of 30% keeping one neuron in the output layer. The retained weight of neurons is set to withstand co-adaptations in order to check the ability of neuron weights to be tuned for specific features of other retained neurons. With this, our model is set to achieve better generalization of our forecasting task in order not to overfit the training dataset. Again, as in [26], during the algorithm compilation, we use mean square error as our loss function and "Adam" as our optimizer. We then fit the network with a batch size of 60 to give as our optimized output. We present the application of the bidirectional LSTM in Figure 5.

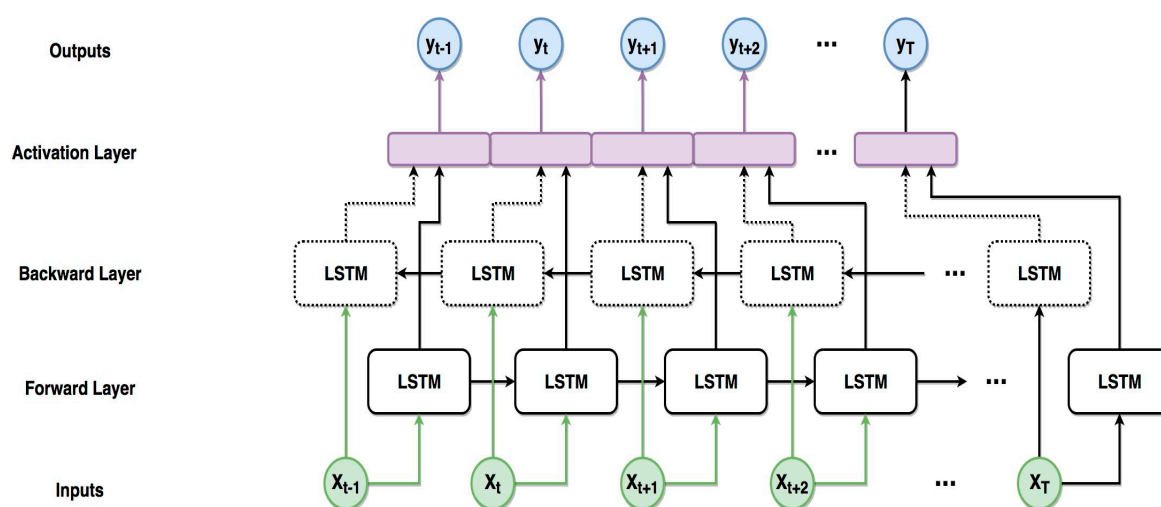


Figure 5. Summary of authors' application of the bidirectional long short-term memory (BiLSTM) technique.

In Figure 5, we initialize our BiLSTM network as:

$$s_0^F = 0, h_0^F = 0 \quad (18)$$

$$s_t^B = 0, h_t^B = 0 \quad (19)$$

With  $x_1, x_2 \dots$  being our inputs; where  $F$  is the forward pass;  $B$  is the backward pass and  $T$  is the time. Propagation in the forward LSTM is set up as:

$$s_t^F, o_t^F = LSTM^F(s_{t-1}^F, o_{t-1}^F, x_t) \forall t \in [1, t] \quad (20)$$

The backward LSTM propagation flow is set up as:

$$s_t^B, o_t^B = LSTM^B(s_{t+1}^B, o_{t+1}^B, x_t) \forall t \in [1, t-1] \quad (21)$$

### 2.5. Error Indexes

Here, we measure errors from our BiLSTM model output using the YoY errors, MAPE, mean absolute deviation (MAD), mean absolute percentage error and root mean square error (RMSE) [26]. Denoting our observed values in a particular year as  $O_t$  and  $F_t$  as our forecasted values in a particular year, the YoY errors is formulated as:

$$\lambda_t = \frac{|O_t - F_t|}{O_t} \quad (22)$$

where  $O_t$  and  $F_t$  are the observed and forecast amount of total CO<sub>2</sub> emissions. Results from Equation (22) are deemed an undercast if  $R_t > F_t$  or of an overcast if  $F_t > R_t$ . We calculate the MAD, MAPE, and RMSE error indexes as:

$$MAD = \frac{\sum_{t=1}^n \lambda_t}{n} \quad (23)$$

$$MAPE = \left[ \frac{100}{n} \left( \sum_{t=1}^n \frac{\lambda_t}{O_t} \right) \right] \quad (24)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (\lambda_t)^2}{n}} \quad (25)$$

where  $n$  is the number of the time period in years.

Although we use MAD and RMSE in evaluating the predictive accuracy of our formulated algorithm, MAPE is used as our main benchmark error index because there are no extreme values in our data sets including zeros.

## 3. Empirical Panel Data Analysis

### 3.1. Cross-Sectional Dependence Analysis

The results of the Pesaran cross-sectional dependence test is shown in Table 2. As it is evident from Table 2 that the  $p$ -value is below 5%, we conclude that cross-sectional dependency should be utilized before stationarity and co-integration relationships are analyzed.

**Table 2.** Cross-sectional dependence test.

Cross-Sectional Dependence Test	Pesaran's Test	$p$ -Value
Pesaran's Test	3.6849	0.0253 <sup>y</sup>

Footnote: <sup>y</sup> represents 5% significance level.

### 3.2. Stationarity Analysis

For the stationarity analysis, we use the Levin, Lin, and Chu (L.L&C), Augmented Dickey–Fuller, IPS and Phillips–Perron Fisher (PP-Fisher) tests. The results of our panel unit root examination are presented in Table 3. From Table 3, we conclude that variables are not stationary at level but stable at first differencing.

**Table 3.** Panel unit root results.

Form	Variables	L.L&C	IPS	ADF	PP-Fisher	Conclusions
Level	lnCO <sub>2</sub>	0.7532 (0.7368)	0.3564 (0.5983)	0.7191 (0.6037)	1.3899 (0.3784)	Non-stationary
	lnGDPC	0.6891 (0.6582)	1.9332 (0.9173)	0.05728 (0.9428)	0.0482 (0.9682)	Non-stationary
	lnLF	−1.2382 (0.2920)	−0.3873 (0.3649)	1.8320 (0.3289)	1.4897 (0.4928)	Non-stationary
	lnGFCF	−0.5803 (0.1893)	0.2894 (0.3702)	1.8739 (0.3492)	1.0478 (0.6397)	Non-stationary
First Difference	ΔlnCO <sub>2</sub>	−1.2513 (0.0392) <sup>y</sup>	−0.9527 (0.0402) <sup>y</sup>	4.6891 (0.0447) <sup>y</sup>	6.8024 (0.469) <sup>y</sup>	Stationary
	ΔlnGDPC	−2.5856 (0.0005) <sup>x</sup>	−1.9274 (0.0264) <sup>y</sup>	6.9357 (0.0317) <sup>y</sup>	10.6134 (0.0021) <sup>x</sup>	Stationary
	ΔlnLF	−1.8397 (0.0001) <sup>x</sup>	−1.3492 (0.0017) <sup>x</sup>	7.9582 (0.0021) <sup>x</sup>	9.5983 (0.0004) <sup>x</sup>	Stationary
	ΔlnGFCF	−0.4294 (0.0203) <sup>y</sup>	−0.1793 (0.0217) <sup>y</sup>	5.8937 (0.0289) <sup>y</sup>	7.6743 (0.0185) <sup>y</sup>	Stationary

Notes: Values in brackets represents the probabilities. <sup>x</sup> represents a 1% significance level and <sup>y</sup> represents a 5% significance level.

### 3.3. Panel Co-Integration Test

After establishing that all our variables employed herein are stationary at first differencing, we perform Pedroni co-integration analysis to check the long-run relationship between our variable data sequences in Table 4. The result of our panel co-integration test reveals that there exist long-run relationship amongst our variables of the study.

**Table 4.** Panel co-integration test result.

Method	Test Statistics	Value	Probability
Pedroni	Panel v-Statistics	−1.4684	0.0294 <sup>y</sup>
	Panel rho-Statistics	−1.1490	0.0379 <sup>y</sup>
	Panel PP-Statistics	−5.8294	0.0071 <sup>x</sup>
	Panel ADF-Statistics	−1.7236	0.0014 <sup>x</sup>
	Group rho-Statistics	−1.6873	0.0117 <sup>y</sup>
	Group PP-Statistics	−7.5832	0.0000 <sup>x</sup>
	Group ADF-Statistics	−1.3848	0.0019 <sup>x</sup>

Notes: <sup>x</sup> indicates 1% level of confidence and <sup>y</sup> indicates 5% level of confidence.

### 3.4. Granger Causality Analysis

Table 5 depicts the results of the Granger causality analysis. Here, we establish that if the probability values in brackets are less than 5% significance level, then there is evidence of a Granger causality relationship. From our analysis, we conclude that there exists a unidirectional causal relationship running from GDPC to CO<sub>2</sub> emissions and from LF to CO<sub>2</sub> emissions. However, there exists no causal relationship between GFCF and CO<sub>2</sub> emissions.



**Table 5.** Results for Granger causality test.

Null Hypothesis	Ghana	Nigeria	Burkina-Faso	Senegal	Benin
lnGDPC does not Granger cause lnCO <sub>2</sub>	8.9482 (0.0029) <sup>x</sup>	12.6892 (0.0021) <sup>x</sup>	4.7492 (0.0278) <sup>y</sup>	5.0254 (0.0178) <sup>y</sup>	4.1394 (0.0278) <sup>x</sup>
lnCO <sub>2</sub> does not Granger cause lnGDPC	1.1274 (0.1585)	1.1946 (0.2742)	0.2172 (0.3673)	0.1734 (0.1949)	0.0978 (0.4822)
lnLF does not Granger cause lnCO <sub>2</sub>	9.7839 (0.0382) <sup>y</sup>	11.2674 (0.0288) <sup>y</sup>	5.0269 (0.0458) <sup>y</sup>	5.9426 (0.0378) <sup>y</sup>	3.4980 (0.0279) <sup>y</sup>
lnCO <sub>2</sub> does not Granger cause lnLF	2.6542 (0.1178)	2.9459 (0.1830)	1.9894 (0.7595)	2.1387 (0.8427)	1.3738 (0.6921)
lnGFCF does not Granger cause lnCO <sub>2</sub>	4.5921 (0.6821)	5.4298 (0.8468)	3.0129 (0.6193)	3.7342 (0.7742)	2.1617 (0.4782)
lnCO <sub>2</sub> does not Granger cause lnGFCF	1.5967 (0.3247)	1.9678 (0.3957)	1.1204 (0.2895)	1.3849 (0.3076)	1.0068 (0.2154)

Notes: the values in brackets indicates the probability values. <sup>x</sup> indicates 1% level of confidence and <sup>y</sup> indicates 5% level of confidence.

#### 4. BiLSTM Testing and Forecasting Analysis

##### 4.1. Testing Stage

First, in order to check the predictive accuracy of our BiLSTM algorithm formulation, we present the BiLSTM test output performance against the observed values for Africa and the selected West African countries. We present the performance of our BiLSTM algorithm formulation against the observed values as well as the error indexes in Figures 6 and 7 respectively.

From Figure 6, our test output for Africa covering our test years performed well as against the observed values (see Figure 6a). BiLSTM test output YoY Errors is ~3.99% for 2006, ~2.18% for 2007; ~1.36% for 2008; ~1.28% for 2009; ~1.11% for 2010; ~0.28% for 2011; ~0.99% for 2012; ~0.87% for 2013; and ~1.13% for 2014. We achieve MAPE accuracy of ~98.53% with a MAD and RMSE value of ~16.54309844 and ~19.57926425, respectively (see Figure 7). For Ghana, the performance of our BiLSTM test output on the observed values are presented in Figure 6b. BiLSTM output for the testing stage YoY errors for Ghana is ~5.96% for 2006; ~2.43% for 2007; ~3.35% for 2008; ~4.50% for 2009; ~2.58% for 2010; ~2.24% for 2011; ~1.41% for 2012; ~2.10% for 2013; and ~1.27% for 2014. MAPE accuracy of ~97.58% is achieved with a MAD and RMSE value of ~0.228479179 and ~0.257513613, respectively (see Figure 7). Nigeria's BiLSTM testing stage output performance on observed values is presented in Figure 6c. The YoY errors for Nigeria is ~3.53% for 2006; ~2.21% for 2007; ~2.40% for 2008; ~2.13% for 2009; ~1.64% for 2010; ~3.08% for 2011; ~1.09% for 2012; ~3.25% for 2013; ~1.92% for 2014. MAPE accuracy of ~97.63% is achieved with a MAD and RMSE of ~2.02728923 and ~2.146268084, respectively (see Figure 7). We present Burkina Faso's testing stage BiLSTM testing stage output and its performance against the observed values in Figure 6d. Burkina Faso's YoY errors spanning 2006 to 2014 is ~13.24%; ~8.20%; ~7.11%; ~5.52%; ~6.37%; ~6.90%; ~7.60%; ~4.24%; and ~5.71%, respectively. We achieve MAPE accuracy of ~92.78% with a MAD and RMSE of ~0.132274181 and ~0.134805768, respectively (see Figure 7). For Senegal, our BiLSTM test output performance on the observed values is presented in Figure 6e. Burkina Faso's YoY errors are ~6.82% for 2006; ~2.38% for 2007; ~4.39% for 2008; ~4.92% for 2009; ~3.20% for 2010; ~1.42% for 2011; ~2.07% for 2012; ~3.16% for 2013; and ~1.35% for 2014. MAPE accuracy of ~96.70% is achieved with a corresponding MAD and RMSE of ~0.182577 and ~0.193074381, respectively (see Figure 7). Benin's BiLSTM testing stage output performance on the observed values is presented in Figure 6f. Benin's YoY errors covering the period from 2006 to 2014 are ~7.51%; ~3.40%; ~5.37%; ~5.80%; ~7.80%; ~0.30%; ~3.78%; ~1.67% and ~1.65%, respectively. We achieve MAPE accuracy of ~95.86% with a MAD and RMSE of ~0.178489815 and ~0.204477393, respectively (see Figure 7).

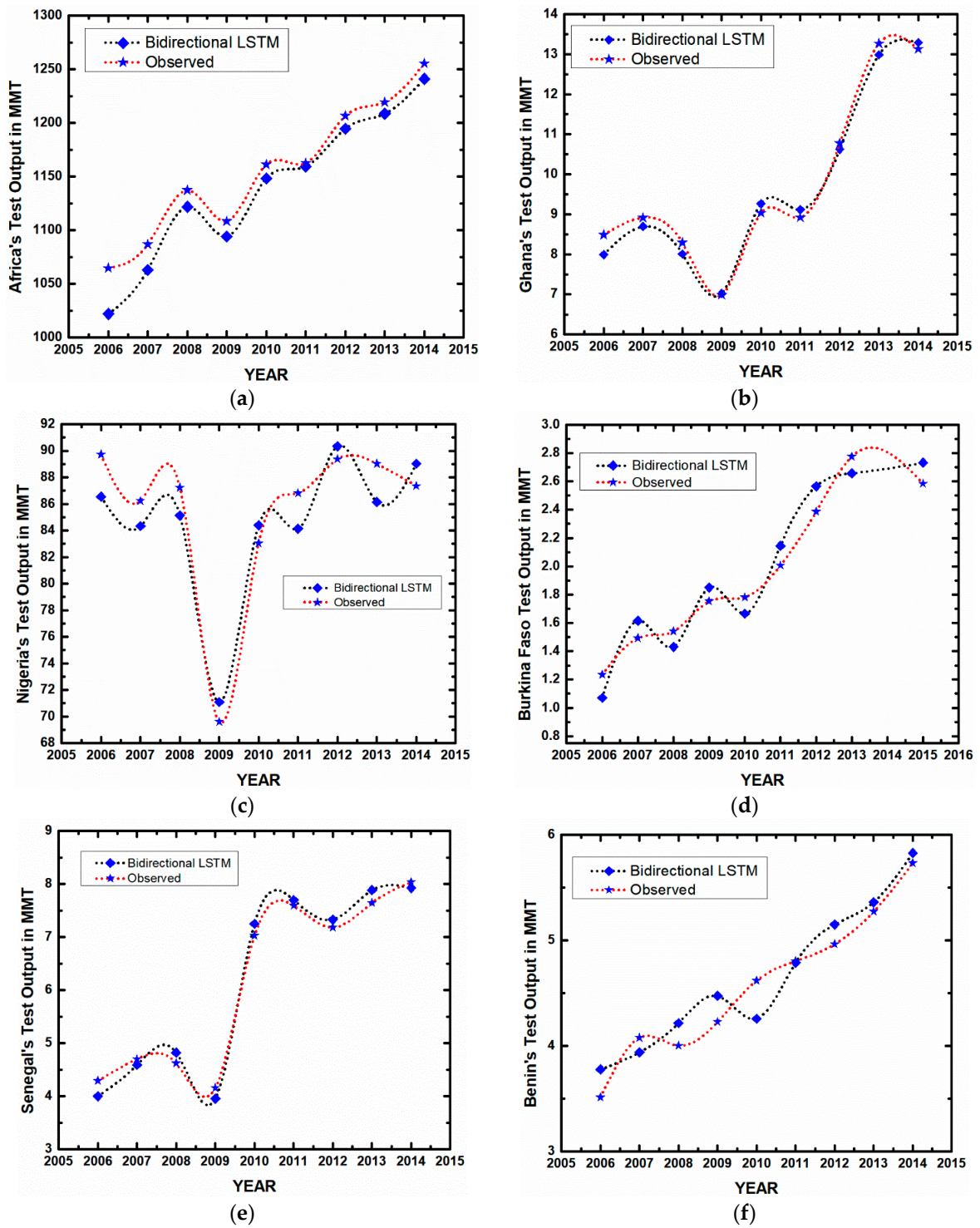


Figure 6. BiLSTM model output against observed values for the period covering 2006–2014.

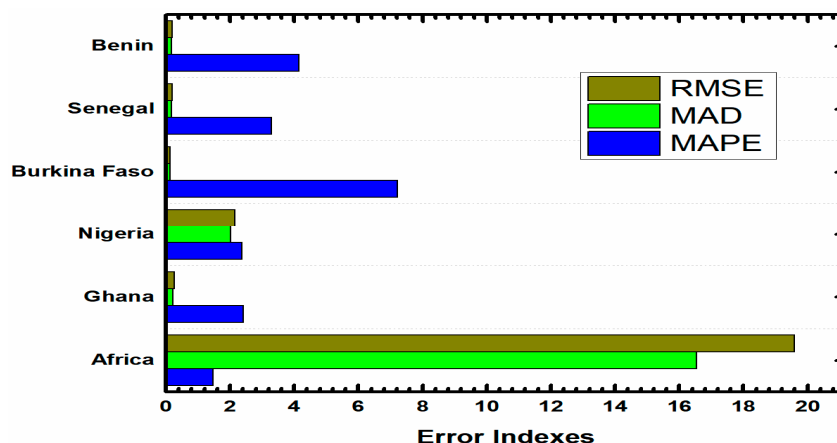


Figure 7. Error indexes of BiLSTM output against observed values.

According to the results obtained, our initial threshold that if the MAPE for the selected West African countries is above 90%, we will make long-term projections to the year 2020 is achieved. However, for Africa’s data, we compare our BiLSTM output against previous IEOs in Table 6. However, because the previous IEOs did not make forecast projections for all the years of the testing stage, we are unable to compute the MAPE, RMSE and MAD. Nevertheless, we present the YoY errors for the years we obtained IEO forecast projections.

Here, our test output for Africa is compared with IEO2010, IEO2013 and IEO2011 projections. We compare the YoY errors for both the BiLSTM test output and previous IEO editions projections against the observed values for the year 2006, 2007, 2009, 2010, 2011 and 2012 in Table 6. YoY errors for each of the years indicates that the BiLSTM outperformed IEO projections. Our technique presents an improvement of ~2-fold, ~3-fold, ~4-fold, ~7-fold, ~13-fold and ~2-fold for the year 2006, 2007, 2009, 2010, 2011 and 2012 respectively.

Table 6. International Energy Outlook (IEO) and BiLSTM year-over-year (YoY) errors.

IEO2010 (Africa in MMT)					
2006			2007		
Observed	BiLSTM	IEO Projection	Observed	BiLSTM	IEO Projection
1064.547	(1021.971)	988	1086.893	(1063.184)	1011
YoY Error					
0.040		0.072		0.022	
				0.070	
IEO2013 (Africa in MMT)					
2009			2010		
Observed	BiLSTM	IEO Projection	Observed	BiLSTM	IEO Projection
1108.286	(1094.129)	1047	1161.128	(1148.208)	1070
YoY Error					
0.013		0.055		0.011	
				0.078	
IEO2011 (Africa in MMT)					
2011			2012		
Observed	BiLSTM	IEO Projection	Observed	BiLSTM	IEO Projection
1162.475	(1159.231)	1120	1206.576	(1194.608)	1184
YoY Error					
0.003		0.040		0.010	
				0.019	



#### 4.2. Forecasting Stage

For Africa's total CO<sub>2</sub> emissions, IEO2017 [57] makes projections for the year 2015 and 2020. Thus, we present future projections for both BiLSTM and IEO2017. As it is evident that our testing stage model output YoY values outperformed previous IEO editions projections for Africa coupled with our algorithm's ability to satisfy the MAPE 90% accuracy threshold initially specified, we make future projections for Africa and the selected West African countries adopted in this study. For the selected country-cases, we present BiLSTM output just for the period covering 2015 to 2020 since there are no country-case projections for total CO<sub>2</sub> emissions available. For Africa's total CO<sub>2</sub> emissions, BiLSTM reports ~1283 MMT for 2015, ~1313 MMT for 2016, ~1343 MMT for 2017, ~1374 MMT for 2018, ~1405 MMT for 2019, and ~1438 MMT for 2020. IEO2017 total CO<sub>2</sub> emissions projections for the year 2015 and 2020 are ~1251 MMT and ~1370 MMT respectively. For each of the West African countries, the BiLSTM projections for Ghana are ~13.83 MMT for 2015, ~14.07 MMT for 2016, ~14.01 MMT for 2017, ~14.81 MMT for 2018, ~14.99 MMT for 2019, and ~15.12 MMT for 2020. Projections for Nigeria are ~86.75 MMT for 2015, ~87.32 MMT for 2016, ~87.75 MMT for 2017, ~88.47 MMT for 2018, ~88.58 MMT for 2019, and ~88.43 MMT for 2020. For Burkina Faso, we estimate ~2.62 MMT for 2015, ~2.47 MMT for 2016, ~2.65 MMT for 2017, ~2.68 MMT for 2018, ~2.66 MMT for 2019, and ~2.71 MMT for 2020. For Senegal, ~8.24 MMT, ~8.55 MMT, ~8.16 MMT, ~8.68 MMT, ~8.72 MMT, and ~8.94 MMT is projected for 2015, 2016, 2017, 2018, 2019 and 2020 respectively. For Benin, BiLSTM projects ~5.89 MMT for 2015, ~6.11 MMT for 2016, ~6.17 MMT for 2017, ~6.20 MMT for 2018, ~6.22 MMT for 2019, and ~6.23 MMT for 2020. We present BiLSTM and IEO2017 projections in Figure 8.

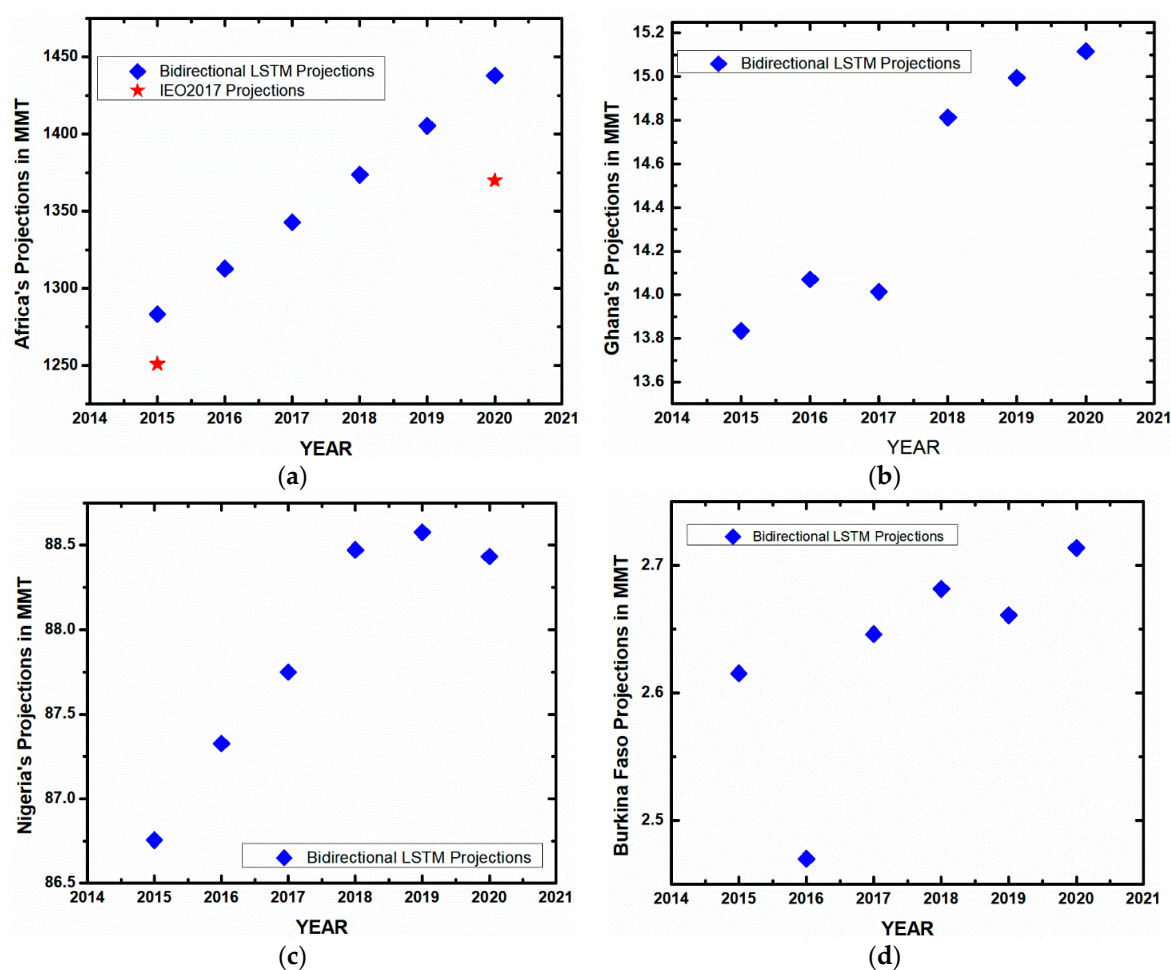
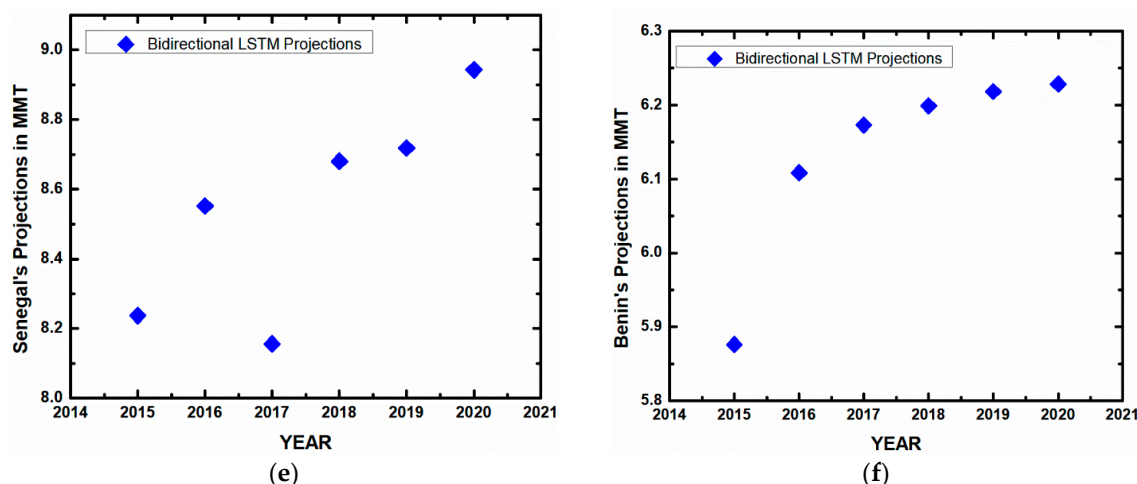


Figure 8. Cont.





**Figure 8.** BiLSTM and IEO2017 forecast projections for Africa (a), BiLSTM projections for Ghana (b), Nigeria (c), Burkina Faso (d), Senegal (e), and Benin (f).

## 5. Discussion

Energy is the spine of the socio-economic development and human welfare of a country [39]. Shortages in the supply of energy are likely to impose an adverse impact on an economy, especially in the developing and emerging countries [58]. However, production of energy from its sources emits harmful toxins into the environment that endanger humans and ecological safety. Due to this, analyzing the nexus between CO<sub>2</sub> emissions and economic growth is crucial to formulating and enacting sustainable policy measures in ensuring an emission-free environment. Literature analyzing the causal relationship between these two variables is extensive. For example; uni-directional causality running from CO<sub>2</sub> emissions to economic growth was found by [59]. Also, by employing the error correction model (ECM), Kasperowicz [60] concluded that economic growth impels the intensive usage of energy-related resources which results in increasing CO<sub>2</sub> emissions. Using ECM estimation, a negative effect was found for the long-run relationship between GDP and CO<sub>2</sub> emissions but the short-run relationship between GDP and CO<sub>2</sub> emissions was found to be positive. Furthermore, by using simultaneous-equations models with panel data of 14 Middle East and North Africa (MENA) countries, Anis [61] concluded that there exists a bidirectional causal relationship between economic growth and CO<sub>2</sub> emissions. However, after establishing the nexus between CO<sub>2</sub> emissions and economic growth, most research papers we have come across on Africa fail to provide researchers, stakeholders and policymakers with an estimation of the future amount of total CO<sub>2</sub> emissions into the environment. After extensive literature searches, we have not come across on original research paper forecasting total CO<sub>2</sub> emissions with an author's own formulated algorithm. In order to fill this gap, we have forecasted Africa and some selected West African countries total CO<sub>2</sub> emissions by formulating an algorithm based on BiLSTM.

Most certainly, the high-accuracy forecast of total CO<sub>2</sub> emissions is crucial to strategizing and implementing reliable and sustainable policies for environmental safety [62,63]. Emissions of global warming gases continue to rise as Africa burns ever more coal, oil and gas for energy [64]. The upward surge in Africa's total CO<sub>2</sub> emissions is a threat to human and ecological safety if past and current intricate paths in data are transmitted into the future. Therefore, forecasting total CO<sub>2</sub> emissions in Africa is required to help governments and stakeholders enact and implement effective policies. However, although the EIA's IEO reference case scenario represents the most credible state of an economic deterministic trend, inaccuracies of past projections affect the implementation of core strategies aimed at curbing or reducing to an appreciable level harmful toxins released into the environment. Based on this background, we propose and use the BiLSTM technique for our testing and forecasting stage. Our network output YoY errors outperform the EIA's IEO previous projections.

Also, after comparing our network output against the observed values for the testing stage, our values do not deviate so much from the observed values. Thus, we present the YoY errors of our output on the observed values in Figure 9. The high accuracy achieved in the proposed BiLSTM technique in Figure 9 is ascribed to the zero assumption-driven variables used and the ability of the technique to keep track of the volatilities in the intricate data trends.

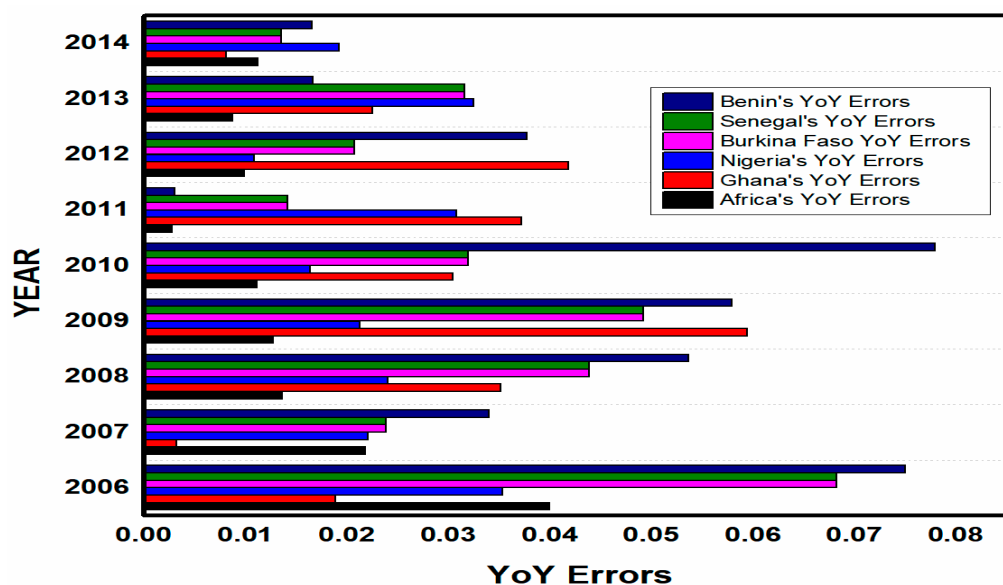


Figure 9. YoY errors of BiLSTM on the observed values.

With substantial evidence on the predictive accuracy of our BiLSTM algorithm formulation, it would be viable to compare our BiLSTM test output with research that has formulated an algorithm for predicting Africa's total CO<sub>2</sub> emissions. However, since literature in this subject matter is lacking, we could only compare our projections with previous IEO projections for Africa. Also, for the selected West African countries employed in this study, we only check the performance of our output against the observed values since previous IEOs did not capture country-case scenarios. Therefore, with our algorithm formulation explained in the material and method section, researchers can replicate our algorithm or formulate a new deep learning algorithm to compare the predictive accuracy of their algorithm with ours. Formulating or replicating our algorithm helps provide policymakers and stakeholders with in-depth information on the future total amount of CO<sub>2</sub> emissions in order to lay down strategic tools aimed at curbing or reducing emissions to an appreciable level for the ultimate goal of sustainability.

## 6. Conclusions and Policy Recommendations

This paper first investigated the relationship between total CO<sub>2</sub> emissions, GDPC, LF, and GFCF in Africa and some selected West African countries spanning from 2007 to 2014. The main conclusions drawn from our panel data analysis is the existence of unidirectional causality running from GDPC to CO<sub>2</sub> emissions and from LF to CO<sub>2</sub> emissions. However, no evidence of causality was found between CO<sub>2</sub> emissions and GFCF. Therefore, with reference to the results obtained, the selected West African countries should diversify into alternative energy sources with lower greenhouse gas emissions. This will assist in reducing CO<sub>2</sub> emissions and at the same sustain long-run economic growth. Also, with respect to the long-run co-integration relationships evident in this study, suggestions for sustainable economic growth in African countries should revolve around the promotion of energy efficiency and the development of clean renewable energy. Furthermore, a new comprehensive evaluation system for economic development should be established in the selected countries in West Africa that aims to reduce pollutant emissions on the environment.

Second, emissions of harmful toxics into the environment have attracted much attention due to the gradual transition to an emission-free environment [65]. However, past forecast imprecision is somewhat high due to assumption-driven causal variables used in core modules. Imprecisions in previous forecasts raise concerns which may force policymakers to be reluctant in implementing environment-related policies. Thus, after analyzing the nexus between total CO<sub>2</sub> emissions, GDPC, LF, and GFCF, we proposed the BiLSTM algorithm for forecasting CO<sub>2</sub> emissions for Africa and some selected West African countries. Our BiLSTM algorithm records significant improvement on previous IEO projections. As total CO<sub>2</sub> emissions in Africa and some selected West African countries employed herein are on the rise according to data trends and from our future projections, we first give readers fair idea about previous and recent measures outlined to mitigate CO<sub>2</sub> emissions and further propose policy recommendations that should be adopted by policymakers to intensify the emission-free environment.

In 2017, the African Development Bank (ADB) through its investments in renewable energy emphasized its commitment to clean energy and efficiency. An initiative entitled The Africa Renewable Energy Initiative (AREI) is tasked to deliver 300 Gigawatts (GW) of renewable energy in 2030 and 10 GW by 2020. With this initiative launched, the G7 has promised to commit US\$10 billion to support the initiative, which came out of COP 21 and subsequently was approved by the African Union. The ADB has also administered The Sustainable Energy Fund for Africa (SEFA) which is a multi-donor trust fund anchored in a commitment of USD 60 million by the governments of Denmark and the United States to support small and medium-scale renewable energy and energy efficiency (EE) projects in Africa. For country case scenarios, the ADB is doing its utmost best to land deals to change the phase of Africa's energy sector. To mention a few, the Côte d'Ivoire Singrobo-Ahouaty project involves the design, construction and operation of a 44-MW hydropower plant which intends to significantly raise its hydropower generation capacity. At the 19th Board Meeting in Songdo, South Korea, the board of the Green Climate Fund (GCF) approved the first funding proposal of the ADB for Zambia's Renewable Energy Financing Framework. The GCF provided a US\$50 million loan and a US\$2.5 million grant which aims to finance 100 MW of renewable energy projects under the renewable energy feed-in-tariff (REFiT) policy of Zambia. Also, the emerging concern for carbon emissions and sustainable development has created an opportunity for renewable energy on the continent of West Africa. The Economic Community of West African States (ECOWAS) due to such concern has developed rural renewable energy development agendas. ECOWAS members target nearly 20% for the renewable makeup of energy by 2030, which includes off-grid electricity serving 25% of the rural population. Although ECOWAS member states have agreed on a binding renewable energy goal, we are abreast of the fact that each country has different legislation on emissions and emissions control. Therefore, country-case recommendations are addressed further by proposing solutions to emission mitigation.

Africa as a continent should adopt the cap-and-trade system in ensuring an emission-free environment. For the cap-and-trade system, policymakers in Africa have to establish a limit or 'cap' on the overall amount of total CO<sub>2</sub> emissions that can be emitted each year. Also, the carbon tax policy should be adopted. Under the carbon tax policy, high taxes should be imposed on firms emitting high harmful toxics into the environment. After imposing the taxes, firms in Africa covered by the 'cap' would weigh the cost of reducing their emissions against the tax they would pay if they kept emitting at their present level. As Ghana's INDC identifies emission reduction actions to be undertaken between 2020 and 2030 in the field of energy, Ghana should increase renewable energy penetration, scale up adoption of efficient energy-saving technologies, and improve forest and solid waste management. Nigeria being the largest emitter of CO<sub>2</sub> emissions should implement mitigation measures that will promote low carbon as well as sustainable and high economic growth, strengthen national institutions and mechanisms (policy, legislative and economic) to establish a suitable and functional framework for climate change governance, and significantly increase public awareness which involves private sector participation in addressing the challenges of climate change. Burkina Faso should reduce the pressure

on ligneous resource through forestry development in order to achieve sustainable production of wood energy and to promote energy economies by the use of improved energy technologies. Also, energy options in Burkina Faso should connect with the electrical network to renewable energies power plants in order to develop both the community and the individual photovoltaic system for the ultimate aim of sustaining the reduction of CO<sub>2</sub> emissions. Senegal should manage energy supply through the implementation of and strengthen actions aimed at optimizing renewable energy demand–supply systems as well as controlling the use of fossils in the sectors of electricity, domestic fuel and transport. Lastly, in order to reduce to an appreciable level Benin’s CO<sub>2</sub> emissions, Benin should intensify its already set up production of non-polluting energy from agricultural residues. Intensifying production of non-polluting energy from agricultural residues will enhance the use of an enormous amount of biomass waste from agricultural production for electricity generation through the use of biomass gasifiers. This is likely to be an effective strategy for diversifying alternative and sustainable sources of energy.

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## References

1. Aye, G.C.; Edoja, P.E. Effect of economic growth on CO<sub>2</sub> emission in developing countries: Evidence from a dynamic panel threshold model. *Cogent Econ. Financ.* **2017**, *90*, 1–22. [[CrossRef](#)]
2. Huesemann, M.H.; Huesemann, J.A. Will progress in science and technology avert or accelerate global collapse? A critical analysis and policy recommendations. *Environ. Dev. Sustain.* **2008**, *10*, 787–825. [[CrossRef](#)]
3. Cherniwchan, J. Economic growth, industrialization, and the environment. *Resour. Energy Econ.* **2012**, *34*, 442–467. [[CrossRef](#)]
4. Lu, W. Greenhouse Gas Emissions, Energy Consumption and Economic Growth: A Panel Cointegration Analysis for 16 Asian Countries. *Int. J. Environ. Res. Public Heal.* **2017**, *14*, 1436. [[CrossRef](#)] [[PubMed](#)]
5. Chandran Govindaraju, V.G.R.; Tang, C.F. The dynamic links between CO<sub>2</sub> emissions, economic growth and coal consumption in China and India. *Appl. Energy* **2013**, *104*, 310–318. [[CrossRef](#)]
6. Dollar, D.; Kleineberg, T.; Kraay, A. Growth still is good for the poor. *Eur. Econ. Rev.* **2016**, *81*, 68–85. [[CrossRef](#)]
7. Di Fonzo, M.; Collen, B.; Mace, G.M. A new method for identifying rapid decline dynamics in wild vertebrate populations. *Ecol. Evol.* **2013**, *3*, 2378–2391. [[CrossRef](#)] [[PubMed](#)]
8. Mohiuddin, O.; Asumadu-sarkodie, S.; Obaidullah, M. The relationship between carbon dioxide emissions, energy consumption, and GDP: A recent evidence from Pakistan energy consumption, and GDP: A recent evidence. *Cogent Eng.* **2016**, *1*, 1–16. [[CrossRef](#)]
9. Höök, M.; Tang, X. Depletion of fossil fuels and anthropogenic climate change—A review. *Energy Policy* **2013**, *52*, 797–809. [[CrossRef](#)]
10. Bissey, S.; Jacques, S.; Le Bunetel, J.C. The fuzzy logic method to efficiently optimize electricity consumption in individual housing. *Energies* **2017**, *10*, 1701. [[CrossRef](#)]
11. Jayaraman, T. The Paris Agreement on Climate Change: Background, Analysis and Implications. *Rev. Agrar. Stud.* **2016**, *5*, 1–31.
12. He, J.K. Global low-carbon transition and China’s response strategies. *Adv. Clim. Chang. Res.* **2016**, *7*, 204–212. [[CrossRef](#)]
13. Reckien, D.; Salvia, M.; Heidrich, O.; Church, J.M.; Pietrapertosa, F.; De Gregorio-Hurtado, S.; D’Alonzo, V.; Foley, A.; Simoes, S.G.; Krkoška Lorencová, E.; et al. How are cities planning to respond to climate change? Assessment of local climate plans from 885 cities in the EU-28. *J. Clean. Prod.* **2018**, *191*, 207–219. [[CrossRef](#)]



14. UNFCCC. United Nations Framework Convention on Climate Change Paris Agreement. In Proceedings of the 21st Session of the Conference of the Parties, Paris, France, 30 November–12 December 2015.
15. Ladislav, S.; Sullivan, M.L.O.; Raimi, D.; Foss, M.M.; Irwin, S.H. Dominance Energy Abundance Market. 2017. Available online: <https://www.oxfordenergy.org/wpcms/wp-content/uploads/2018/01/OEF-111.pdf> (accessed on 31 August 2018).
16. IPCC. *Climate Change 2014: Mitigation of Climate Change*; Cambridge University Press: Cambridge, UK, 2014; pp. 527–532.
17. Wang, C.; Wang, F.; Zhang, X.; Yang, Y.; Su, Y.; Ye, Y.; Zhang, H. Examining the driving factors of energy related carbon emissions using the extended STIRPAT model based on IPAT identity in Xinjiang. *Renew. Sustain. Energy Rev.* **2017**, *67*, 51–61. [[CrossRef](#)]
18. Cho, C.-H.; Chu, Y.-P.; Yang, H.-Y. An Environment Kuznets Curve for GHG Emissions: A Panel Cointegration Analysis. *Energy Sources Part B Econ. Plan. Policy* **2014**, *9*, 120–129. [[CrossRef](#)]
19. Giovanis, E. Environmental Kuznets curve: Evidence from the British Household Panel Survey. *Econ. Model.* **2013**, *30*, 602–611. [[CrossRef](#)]
20. Tang, C.F.; Tan, B.W.; Ozturk, I. Energy consumption and economic growth in Vietnam. *Renew. Sustain. Energy Rev.* **2016**, *54*, 1506–1514. [[CrossRef](#)]
21. Komal, R.; Abbas, F. Linking financial development, economic growth and energy consumption in Pakistan. *Renew. Sustain. Energy Rev.* **2015**, *44*, 211–220. [[CrossRef](#)]
22. Cowan, W.N.; Chang, T.; Inglesi-Lotz, R.; Gupta, R. The nexus of electricity consumption, economic growth and CO<sub>2</sub> emissions in the BRICS countries. *Energy Policy* **2014**, *66*, 359–368. [[CrossRef](#)]
23. Asongu, S.; El Montasser, G.; Toumi, H. Testing the relationships between energy consumption, CO<sub>2</sub> emissions, and economic growth in 24 African countries: A panel ARDL approach. *Environ. Sci. Pollut. Res.* **2016**, *23*, 6563–6573. [[CrossRef](#)] [[PubMed](#)]
24. Abid, M. The close relationship between informal economic growth and carbon emissions in Tunisia since 1980: The (ir)relevance of structural breaks. *Sustain. Cities Soc.* **2015**, *15*, 11–21. [[CrossRef](#)]
25. Ezzo, L.J.; Keho, Y. Energy consumption, economic growth and carbon emissions: Cointegration and causality evidence from selected African countries. *Energy* **2016**, *114*, 492–497. [[CrossRef](#)]
26. Ameyaw, B.; Yao, L. Sectoral Energy Demand Forecasting under an Assumption-Free Data-Driven Technique. *Sustainability* **2018**, *10*, 2348. [[CrossRef](#)]
27. Hu, Y.C.; Jiang, P. Forecasting energy demand using neural-network-based grey residual modification models. *J. Oper. Res. Soc.* **2017**, *68*, 556–565. [[CrossRef](#)]
28. Abdel-Aal, R.E. Univariate modeling and forecasting of monthly energy demand time series using abductive and neural networks. *Comput. Ind. Eng.* **2008**, *54*, 903–917. [[CrossRef](#)]
29. Hamzaçebi, C. Primary energy sources planning based on demand forecasting: The case of Turkey. *J. Energy Southern Afr.* **2016**, *27*, 2–10. [[CrossRef](#)]
30. WIND. Wind-Financial Terminal News. Available online: <http://www.wind.com.cn/en/wft.html> (accessed on 15 July 2018).
31. World Bank. *World Development Indicators 2015*; World Bank: Washington, DC, USA, 2015; ISBN 9780821373866.
32. Canadell, J.G.; Raupach, M.R.; Houghton, R. A Anthropogenic CO<sub>2</sub> Emissions in Africa. *Biogeosciences* **2009**, *6*, 463–468. [[CrossRef](#)]
33. Marchal, V.; Dellink, R.; Van Vuuren, D.; Clapp, C.; Château, J.; Lanzi, E.; Magné, B.; Van Vliet, J. OECD Environmental Outlook to 2050: Climate Change Chapter. 2011. Available online: <https://www.oecd.org/env/cc/49082173.pdf> (accessed on 18 July 2018).
34. Meng, J.; Mi, Z.; Guan, D.; Li, J.; Tao, S.; Li, Y.; Feng, K.; Liu, J.; Liu, Z.; Wang, X.; et al. The rise of South-South trade and its effect on global CO<sub>2</sub> emissions. *Nat. Commun.* **2018**. [[CrossRef](#)] [[PubMed](#)]
35. Davis, S.J.; Caldeira, K. Consumption-based accounting of CO<sub>2</sub> emissions. *Proc. Natl. Acad. Sci. USA* **2010**. [[CrossRef](#)] [[PubMed](#)]
36. Maestas, N.; Mullen, K.J.; Powell, D. The Effect of Population Aging on Economic Growth, the Labor Force and Productivity. 2016. Available online: <http://www.nber.org/papers/w22452> (accessed on 18 July 2018).
37. Ugochukwu, U.S.; Chinyere, U.P. The Impact of Capital Formation on the Growth of Nigerian Economy. *Res. J. Financ. Account.* **2013**, *4*, 36–43.
38. Cobb, C.; Douglas, P. A Theory of Production. *Am. Econ. Rev.* **1928**, *18*, 139–165.

39. Ameyaw, B.; Opong, A.; Abruquah, L.A.; Ashalley, E. Causality Nexus of Electricity Consumption and Economic Growth: An Empirical Evidence from Ghana. *Open J. Bus. Manag.* **2017**, *5*, 1–10. [[CrossRef](#)]
40. Karekezi, S.; Kithyoma, W. Renewable energy development. In Proceedings of the Workshop for African Energy Experts on Operationalising the NEPAD Energy Initiative, Dakar, Senegal, 2–4 June 2003.
41. Pesaran, M.H. General Diagnostic Tests for Cross Section Dependence in Panels. Available online: [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=572504](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=572504) (accessed on 18 July 2018).
42. Breusch, T.S.; Pagan, A.R. The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. *Rev. Econ. Stud.* **1980**, *47*, 239. [[CrossRef](#)]
43. Im, K.S.; Pesaran, M.H.; Shin, Y. Testing for Seasonal Unit Roots in Heterogeneous Panels. *J. Econom.* **2003**, *115*, 53–74. [[CrossRef](#)]
44. Levin, A.; Lin, C.F.; Chu, C.S.J. Unit root tests in panel data: Asymptotic and finite-sample properties. *J. Econom.* **2002**, *108*, 1–24. [[CrossRef](#)]
45. Pedroni, P. Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the PPP hypothesis. *Econom. Theory* **2004**, *20*, 597–625. [[CrossRef](#)]
46. Apergis, N.; Payne, J.E. A time varying coefficient approach to the renewable and non-renewable electricity consumption-growth nexus: Evidence from a panel of emerging market economies. *Energy Sources Part B Econ. Plan. Policy* **2014**, *9*, 101–107. [[CrossRef](#)]
47. Apergis, N.; Payne, J.E. Renewable energy consumption and economic growth: Evidence from a panel of OECD countries. *Energy Policy* **2010**, *38*, 656–660. [[CrossRef](#)]
48. Engle, R.F.; Granger, C.W.J. Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica* **1987**, *55*, 251. [[CrossRef](#)]
49. Granger, C.W.J. Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica* **1969**, *37*, 424. [[CrossRef](#)]
50. International Energy Agency-U.S. Unit Converter. 2016. Available online: <https://www.iea.org/statistics/resources/unitconverter/> (accessed on 15 July 2018).
51. U.S. Energy Information Administration. *International Energy Outlook 2010*; Department of Energy: Washington, DC, USA, 2010.
52. U.S. Energy Information Administration. *International Energy Outlook 2011*; Department of Energy: Washington, DC, USA, 2011.
53. U.S. Energy Information Administration. *International Energy Outlook 2013*; Department of Energy: Washington, DC, USA, 2013.
54. Barone, A.V.M.; Helcl, J.; Sennrich, R.; Haddow, B.; Birch, A. Deep Architectures for Neural Machine Translation. In Proceedings of the Second Conference on Machine Translation, Copenhagen, Denmark, 7–8 September 2017; pp. 99–107.
55. Hou, L.; Samaras, D.; Kurc, T.; Gao, Y.; Saltz, J. ConvNets with Smooth Adaptive Activation Functions for Regression. In Proceedings of the 20th International Conference on Artificial Intelligence and Statistics, Fort Lauderdale, FL, USA, 20–22 April 2017; pp. 430–439.
56. Helmbold, D.P.; Long, P.M. Surprising properties of dropout in deep networks. *J. Mach. Learn. Res.* **2016**, *65*, 1–24.
57. U.S. Energy Information Administration International Energy Outlook 2017. Available online: [www.eia.gov/forecasts/ieo/pdf/0484\(2016\).pdf](http://www.eia.gov/forecasts/ieo/pdf/0484(2016).pdf) (accessed on 18 July 2018).
58. Palamalai, S.; Siddanth, I.; Prakasam, K. Relationship between Energy Consumption, CO<sub>2</sub> Emissions, Economic Growth and Trade in India. *J. Econ. Financ. Stud.* **2015**, *1*, 1–17. [[CrossRef](#)]
59. Lim, K.-M.; Lim, S.-Y.; Yoo, S.-H. Oil Consumption, CO<sub>2</sub> Emission, and Economic Growth: Evidence from the Philippines. *Sustainability* **2014**, *6*, 967–979. [[CrossRef](#)]
60. Kasperowicz, R. Economic growth and CO<sub>2</sub> emissions: The ECM analysis. *J. Int. Stud.* **2015**, *8*, 91–98. [[CrossRef](#)]
61. Anis, O. CO<sub>2</sub> Emissions, Energy Consumption and Economic Growth Nexus in MENA countries: Evidence from Simultaneous Equation Models. *Energy Econ.* **2013**, *40*, 657–664.
62. Wang, Z.; Wang, J.; He, D. Transit Policies and Potential CO<sub>2</sub> Emission Impacts—Some Insights from China’s Transit Priority Policies in Recent Years. *Transp. Res. Board.* **2012**, *19*, 1–14. [[CrossRef](#)]
63. Gu, B.; Tan, X.; Zeng, Y.; Mu, Z. CO<sub>2</sub> Emission Reduction Potential in China’s Electricity Sector: Scenario Analysis Based on LMDI Decomposition. *Energy Procedia* **2015**, *75*, 2436–2447. [[CrossRef](#)]

64. Allali, M.; Tamali, M.; Rahli, M. The Impact of CO<sub>2</sub> Emission on Output in Algeria. *Energy Procedia* **2015**, *74*, 234–242. [[CrossRef](#)]
65. Du, S.; Zhu, L.; Liang, L.; Ma, F. Emission-dependent supply chain and environment-policy-making in the “cap-and-trade” system. *Energy Policy* **2013**, *57*, 61–67. [[CrossRef](#)]



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