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Does energy consumption follow asymmetric behavior? An assessment of Ghana's energy sector dynamics

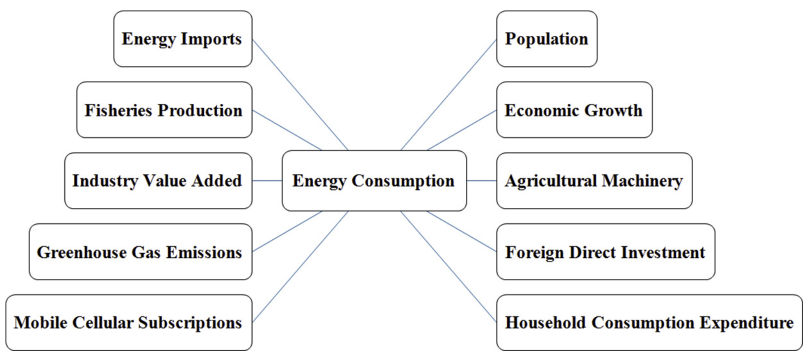
Samuel Asumadu Sarkodie [a,*], Aba Obrumah Crentsil [b], Phebe Asantewaa Owusu [c]

[a] Department of Environmental Sciences, Faculty of Science and Engineering, Macquarie University, NSW 2109 Australia
[b] Institute of Statistical, Social & Economic Research (ISSER), University of Ghana, P.O. Box LG 74, Legon, Ghana
[c] Sustainable Environment and Energy Systems, Middle East Technical University, Northern Cyprus Campus, Kalkanli, Guzelyurt, TRNC 99738/Mersin 10, Turkey

HIGHLIGHTS

- Does energy evolves in different states by transitioning over a finite set of states?
- We ascertain if energy consumption follow an asymmetric behavior.
- We examine the unobserved factors underpinning energy crisis in Ghana.
- Markov-switching, NIPALS regression, and neural network analysis are used.

GRAPHICAL ABSTRACT



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ABSTRACT

The study answered the following questions: First, does energy evolves in different regimes by transitioning over a finite set of unobserved states? Second, does energy consumption follow an asymmetric behavior over “energy boom” and energy scarcity? and, Third, are there unobserved factors underpinning energy crisis? We employed Markov-switching dynamic regression to examine the asymmetric effect, NIPALS regression to examine energy determinants and neural network analysis for prediction. The neural network model suggests a 99% prediction of energy consumption by the predictor variables. It was evident that energy consumption evolves in two states by transitioning over a finite set of unobserved states. The 11.6% growth in energy consumption is expected to occur in 4.1 years while energy crisis is expected to last for 3.7 years. Technological advancement and the development of green energy through foreign direct investment are essential to improve energy sector portfolio.

* Corresponding author.
E-mail address: asumadusarkodiesamuel@yahoo.com (S.A. Sarkodie).

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1. Introduction

Energy production and consumption remain the largest contributor of anthropogenic carbon dioxide emissions, as such, mitigation option requires measures that promote energy efficiency and the substitution of conventional energy sources with renewable energy technologies (Owusu and Asumadu, 2016; Sarkodie and Strezov, 2018). While the Sustainable Development Goal Seven seeks to ensure the availability and accessibility of clean and modern energy technologies (United Nations, 2015), the underlying factors that propel energy consumption levels should not be underestimated.

The determination of factors affecting energy consumption and economic growth has been a topical subject of many studies, since the 1970s. However, the existing evidence on the nexus between economic growth and energy consumption has been inconclusive. Yet, an understanding of the determinants of energy consumption and its modeling in emerging economies is important. Studies on the relationship between energy consumption and economic growth have been found to be very complex due to the four possible impact scenarios, namely (Inglesi-Lotz and Pouris, 2016; Sarkodie and Adom, 2018): growth, conservative, feedback and neutrality hypotheses.

The growth hypothesis postulates a unidirectional causality from energy consumption to economic growth. This implies that energy saving policies may hinder growth because such an economy is dependent on energy to grow. Second, the conservative hypothesis refers to a unidirectional causality from economic growth to energy consumption. Here, energy-saving policies may have little or no negative effects on growth (Destek and Sarkodie, 2019). However, if the causal relationship from energy consumption to growth is positive, the adoption of energy-saving policies can lead to a decline in growth and employment. Conversely, if the causal relationship from economic growth to energy consumption is negative, the use of energy saving policies can lead to an increase in output. The feedback hypothesis refers to a bidirectional causality between energy consumption and economic growth. Thus, energy conservation policies can restrict the economy and vice versa. The neutrality hypothesis argues that there is no causal relationship between energy consumption and economic growth. Accordingly, reducing energy consumption is ineffective for economic growth.

The lack of consensus evidence in energy-growth correlation is primarily due to the omission of other potential determinants in the modeling of energy demand function (Chang, 2015). As such, we propose using econometric methods that allow for the consideration of an asymmetric effect and viable data series in studying the causal factors of energy consumption.

The aim of the study is to answer the following questions: First, does energy evolves in a different state (regime) by transitioning over a finite set of unobserved states? Second, does energy consumption follow an asymmetric behavior over “energy boom” and energy scarcity? Third, are there unobserved factors underpinning energy crisis? and Fourth, what are the probabilities that a country will experience “energy boom” or “energy crisis”?

To the best of our knowledge, no study in existing literature considers trio dynamic models that minimize the complexities of available models in the literature. First, this study overcomes multicollinearity, a problem with time series variables by using both NIPALS and neural network models. Second, the study controls for structural breaks and discontinuous shifts in regression regimes at an unknown point using the Markov-switching dynamic regression. The Markov-switching dynamic regression has been widely used in financial economics (Hamilton, 1989), political (Jones et al., 2010) and health sciences (Martínez-Beneito et al., 2008) but has not been applied in energy economics. Importantly, the Markov-switching dynamic regression can easily switch the states according to the Markov process; the speed of adjustment/correction is quick after a change of state and has the ability to deal with a high number of variable observations. Third, the study draws attention to unobserved variables that play a critical role in energy demand-side management and energy conservation while examining the predictive power of trio models, thus, providing new evidence with policy implications.

The remainder of the study consists of section two “*Literature Review*”, section three “*Methodology*”, section four “*Results and Discussion*”, and section five “*Conclusion*”.

Nomenclature

3G	Third Generation of Broadband Cellular Network Technology
4G	Fourth Generation of Broadband Cellular Network Technology
ARDL	Autoregressive Distributed Lag
GSM	Global System for Mobile communication
ICT	Information and Communication Technology
LMDI	Logarithmic Mean Divisia Index
MAD	Mean Absolute Deviation
MAPE	Mean Absolute Percentage Error
NEPAD	New Partnership for Africa's Development
NIPALS	Nonlinear Iterative Partial Least Squares
OECD	Organisation for Economic Co-Operation and Development
RSME	Root Mean Square Error
SSE	Error Sum of Squares
VECM	Vector Error Correction Model
VIP	Variable Importance of Projection

2. Literature review

An investigation of the causal nexus between economic activities and energy consumption and Greenhouse gas emissions has been studied in several empirical works. According to Sarkodie and Owusu (2016), the majority of the existing literature can be categorized into three; the first category of research, examines the causal effect of environmental pollution, energy consumption, and macroeconomic variables by testing the validity of the environmental Kuznets curve hypothesis.

Using fixed effects model and the method of least square generalized linear regression in China between 1995 and 2010, Zhang and Lin (2012), illustrated that the demographic intensities, GDP, industrial production, and energy consumption have an impact on CO_2 emissions. Ahmed et al. (2016) examined the causal effect of carbon dioxide emissions, GDP, and energy consumption in Brazil, South Africa, China and India using a panel data spanning from 1970 to 2013 using the fully modified least squares method. Their results confirmed the validity of the environmental Kuznets curve hypothesis and found evidence of bidirectional causality between carbon dioxide emissions and energy consumption.

According to (Sarkodie and Owusu, 2016) the second category of research examines the causal effect of environmental pollution, energy consumption, and macroeconomic variables without testing the validity of the environmental Kuznets curve hypothesis. Employing a multivariate co-integration analysis, ARDL and vector error correction modeling techniques to investigate in Ghana for the period 1971–2013, Asumadu and Owusu (2016b) examined the relationship between carbon dioxide emissions, GDP, energy consumption and population. Their results suggested the existence of mutual causality between Ghana's energy consumption and GDP.

Another study by Owusu and Samuel (2016) investigated the relationship between carbon dioxide emissions, energy consumption, population and GDP in Ghana using VECM technique for the period 1980–2012. Their findings suggested that the continuous increase in population growth within the study period has resulted in a substantial increase in energy demand and CO_2 emissions in Ghana. A bidirectional causality was observed between carbon dioxide emissions and energy consumption.

In the same way, Mohiuddin et al. (2016) examined the relationship between carbon dioxide emissions, energy consumption (EC), GDP, and electricity production from oil, coal and natural gas, in Pakistan from

1971 to 2013 and found evidence of long-run equilibrium relationship running from EC, electricity production from coal, electricity production from natural gas, electricity production from oil and GDP to carbon dioxide emissions.

The third category of research according to (Sarkodie and Owusu, 2016) examines the causal effect of environmental pollution and agricultural variables. Using Chinese official statistical data, Zou et al. (2015), investigated the emissions of greenhouse gases from agricultural irrigation to inform strategies for reasonable use of water resources and emission reduction. The study found out that the total carbon dioxide equivalent (CO_2-e) emission from agricultural irrigation is 36.72–54.16 Mt. Emissions from energy activities in irrigation (including water pumping and conveyance) account for 50%–70% of total emissions from energy activities in the agriculture sector. Groundwater pumping was the biggest emission source, accounting for 60.97% of total irrigation emissions.

Similarly using the LMDI technique, Li et al. (2014) investigated agricultural CO_2 emissions in China from 1994 to 2011. Their findings suggested that economic development acts to increase CO_2 emissions significantly whiles Agricultural subsidy acts to reduce CO_2 emissions effectively.

The fourth category of research (Faucheux and Nicolaï, 2011; Hamdi et al., 2014; Moyer and Hughes, 2012) examines the causal effect of energy consumption, CO_2 emission, and information communication technology usage. Employing panel unit root test accounting for the presence of cross-sectional dependence, a panel cointegration test, the Pooled Mean Group regression technique and Dumitrescu-Hurlin causality test, Salahuddin and Alam (2016) examined the short- and long-run effects of ICT use and economic growth on electricity consumption using OECD panel data for the period of 1985 to 2012. Their findings suggested electricity consumption in both the short- and the long-run had a direct relationship to the use of ICT and economic growth. In a similar study using data for a period of 1985–2012 in Australia, Salahuddin and Alam (2015) examines the short- and long-run effects of Internet usage and economic growth on electricity. Their results indicated the presence of a unidirectional between Internet usage to economic growth and electricity consumption.

Examining the trend of worldwide electricity consumption Van Heddeghem et al. (2014) and showed that three key ICT categories, namely, communication networks, personal computers, and data centers, has increased in 2012 from its level in 2007 due to increase in electricity consumption.

The majority of the aforementioned literature assured the existence of a closed-form relationship between energy consumption and macroeconomic factors mostly, focusing on a casualty with less than three variables. As a contribution to literature, an attempt is made to investigate the causal relationship between energy consumption, agricultural machinery, foreign direct investment net inflows, economic growth, total greenhouse gas emissions, industrialization, total fisheries production, net energy imports, electric power transmission and distribution losses, household final consumption expenditure, mobile cellular subscriptions, and population using time series data from 1971 to 2014 in Ghana.

3. Methodology

3.1. Data

To conduct an assessment of energy consumption in Ghana, the study employs data from 1971 to 2014 from the World Bank World Development Indicator database (World Bank, 2016). Twelve data variables are used in the study namely; Total greenhouse gas emissions (kt of CO_2 equivalent), Energy consumption (kg of oil equivalent per capita), GDP (current LCU), Mobile cellular subscriptions, Population, Total fisheries production (metric tons), Industry, value added (current US$) as a proxy for industrialization, Household final consumption expenditure (current LCU), Foreign direct investment, net inflows (% of GDP), Energy imports, net (% of energy use), Agricultural machinery and Electric power transmission and distribution losses (% of output) presented in Table 1. Energy use employed as a proxy for energy consumption is defined by the World Bank as "*the use of primary energy before transformation to other end-use fuels, which is equal to indigenous production plus imports and stocks change, minus exports and fuels supplied to ships and aircraft engaged in international transport*" (World Bank, 2016). Fig. 1 presents the trend of the study variables. A visual assessment of Fig. 1 shows that the trend of the variables exhibits some unexplainable behaviors and complexities that can only be ascertained through a dynamic regression model elaborated in the subsequent section.

3.2. Model estimation

3.2.1. Markov-switching dynamic regression

The Markov-switching dynamic regression model was initiated by Goldfeld and Quandt (1973); Quandt (1972) and was first employed by Hamilton (1989) in economics to examine the observed asymmetric behavior in the growth rate of GDP. The Markov-switching dynamic regression model is "rich enough" to capture the dynamic and switching behavior of macroeconomic and energy-related variables thus, allows quick adjustment/correction of the state classification measures (Hamilton, 1989; Zhu et al., 2017).

The general specification of the Markov-switching dynamic regression model is expressed as:

$$Y_t = \varphi_s + X_t\alpha + Z_t\beta_s + \varepsilon_s \tag{1}$$

where Y_t is the dependent variable, φ_s is the "state-dependent" intercept, X_t and Z_t represent exogenous variables in a vector form, α represents the "state-invariant" coefficients, β_s is the "state-dependent" coefficients and ε_s represents the independent and identically distributed normal error with a "state-dependent" variance σ_s^2 and a zero mean.

The two-state Markov state-switching model considers that the response of the independent variables' return to structural energy consumption shocks is dependent on the state (S_t) at time (t). S_t denotes an observable two-state and 1st order Markov process. The transition probability of the two-state is expressed in a matrix as:

$$P = \begin{pmatrix} p11 & p21 \\ p12 & p22 \end{pmatrix} \tag{2}$$

where $p_{ij} = P(S_t = j|S_{t-1} = i)$, by means of $\sum_{j=1}^{2} p_{ij} = 1$, i $(i = 1,2)$ denotes the number of states involved in the Markov process.

3.2.2. Neural network

The neural network is a function of some hidden nodes derived from the non-linear functions of the original inputted variables.

Table 1
Data variable description.

Variable name	Variable code
Total greenhouse gas emissions (kt of CO_2 equivalent)	GHG
Energy consumption (kg of oil equivalent per capita)	ENUS
GDP (current LCU)	GDP
Mobile cellular subscriptions	MCS
Population	POP
Total fisheries production (metric tons)	TFP
Industry, value added (current US$)	INA
Household final consumption expenditure (current LCU)	HFICE
Foreign direct investment, net inflows (% of GDP)	FDIN
Energy imports, net (% of energy use)	EGIM
Agricultural machinery	AGM
Electric power transmission and distribution losses (% of output)	EPTDL

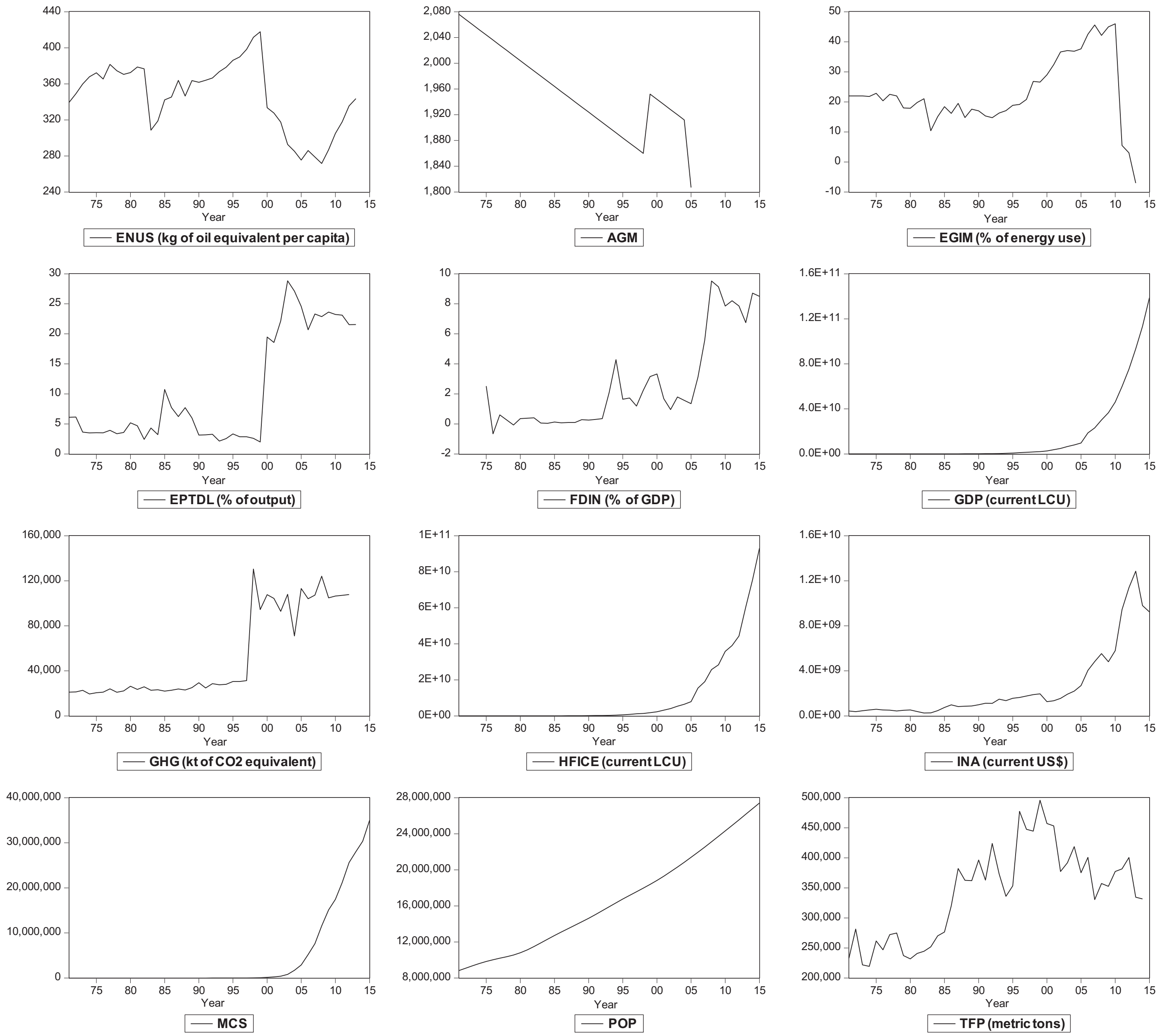

Fig. 1. Trend of variables.

A one-layer feed-forward neural network employed in the study is expressed as:

$$PredENUS = f\left(\varepsilon_o + \sum_{j=1}^{k} \boldsymbol{h}\left(\varphi_j + \sum_{i=1}^{n} X_i w_{ij}\right)\varepsilon_j\right) \tag{3}$$

where *PredENUS* is the predicted values of energy consumption representing the neural network output, $f(.)$ is the non-linear transfer function of the independent variables (inputs) X_i, $h(.)$ is the hidden layer activation function applied to the nodes with corresponding biases of the hidden layer φ_j, w_{ij} denotes the weight from the input layer to the hidden layer, ε_o and ε_j represent the output biases and the weight values from the hidden layer to the output layer.

3.2.3. NIPALS regression

The Nonlinear Iterative Partial Least Squares (NIPALS) regression analysis by Sarkodie and Adom (2018); Wold et al. (2001) begins with the centering and scaling of the dependent variable (Y) and independent variables (X). The next step involves the initialization of $u = Y$ with a subsequent repetition of Eqs. (4)–(9) to reach convergence thus,

$$w = X'u/(u'/u) \tag{4}$$

$$w{:=}w/\|w\| \tag{5}$$

$$t = Xw \tag{6}$$

$$c = Y't/(t'/t) \tag{7}$$

$$c{:=}c/\|c\| \tag{8}$$

$$u = Yc \tag{9}$$

where w and c are the X and Y loadings with a unit norm thus, c is a 1×1 unit vector converging in a single NIPALS iteration while t and u are the X and Y scores.

Subsequently, X and Y are regressed on t and u as:

$$p = X't/(t'/t) \tag{10}$$

$$q = Y'u/(u'/u) \tag{11}$$

The next step is a deflation of the matrices of X and Y expressed as:

$$X{:=}X-tp' \tag{12}$$

$$Y{:=}Y-tc' \tag{13}$$

The deflation of the matrices is repeated d times gathering the vectors (t, p, u, q) into matrices to produce a preferred factorization into X and Y scores **T** and **U**, X and Y loadings **P** and **Q**, weights of X and Y **W** and **C** derived by gathering **w** and **c** vectors into $n \times d$ and $m \times d$ matrices and output errors/residuals **E** and **F** expressed as:

$$X = TP' + E \tag{14}$$

$$Y = UQ' + F \tag{15}$$

To predict Y from X, the matrix of the regression coefficient (B) is expressed as:

$$B = W \times C' \tag{16}$$

Therefore, the final NIPALS regression is given as:

$$\hat{Y} = XB^* + (\mu_Y - \mu_X B^*) \tag{17}$$

where

$$B^* = \Sigma_X{}^{-1} B \Sigma_{Y'} E^* = E \Sigma_{X'} \tag{18}$$

4. Results and discussion

4.1. Descriptive analysis

This section begins with a descriptive statistical analysis of the study variables presented in Table 2. The average energy consumption within the last four decades was almost 347 kg of oil equivalent per capita, a minimum and maximum consumption of 272 and 418 kg of oil equivalent per capita. Total greenhouse gas emissions experienced a rise from 19,454 kt of CO_2 equivalent to 130,473 kt of CO_2 equivalent with an average of 45,194 kt of CO_2 equivalent. Economic growth grew from almost GH₵ 250,000 in 1971 to GH₵ 113 billion in 2014 with a mean of GH₵ 12.3 billion. Mobile cellular subscriptions (i.e. MTN, Vodafone, Tigo, Airtel, and Expresso) has experienced a significant growth in the communication industry from zero in 1971 to 30,360,771 in 2014 at an average of 3,826,884 subscriptions. It is important to note that mobile cellular subscription is employed as a proxy for assessing the trend of mobile phone usage in Ghana. There has been an exponential growth in population, from 8,827,273 to 26,786,598 in 2014 at an average growth of 16,307,944 people. Since Ghana is an agrarian country, the use of agricultural machinery grew from 1807 tractors to 2, 076 tractors, with a mean of 1957 tractors and the total fisheries production appreciated from at least 219,327 metric tons to a maximum of 495,683 metric tons at an average of 341,821 metric tons. The economic value of industrialization has increased from US$ 252,000,000 to US$ 12,900,000,000 with a mean of US$ 2,380,000,000. There has been a huge increase in household final consumption expenditure from GH₵ 193,500 to GH₵ 75.5 billion with a mean of GH₵ 8.64 billion. Foreign direct investment net inflows grew from −1% of GDP to 10% of GDP at a mean of 2%. Ghana's net energy imports grew from −7% of energy use to 40% of energy use, with an average of 23% of energy use. Electric power transmission and distribution losses grew from 2% of output to 29% of output, with an average of 10% of output energy production. Table 2 reveals that except for energy consumption, the remaining variables are positively skewed. Apart from EGIM, FDIN, GDP, HFICE, INA, and MCS, the remaining variables exhibit a platykurtic distribution. It is further revealed that only ENUS, AGM, EGIM and TFP are normally distributed hence, the application of a logarithmic transformation to the study variables. The correlation analysis reveals that except AGM, FDIN, and TFP, the remaining variables have a negative relationship with energy consumption. However, due to the limitation of correlation as a descriptive analysis and its inability to determine the causal factors, the study proceeds with inferential statistical analysis.

4.2. Unit root test

According to Perron (1989), unit roots and structural breaks have a close relationship, thus, traditional unit root tests are "*biased towards false unit root null when the data are trend stationary with a structural*

Table 2
Descriptive statistical analysis.

Statistic	ENUS	AGM	EGIM	EPTDL	FDIN	GDP	GHG	HFICE	INA	MCS	POP	TFP
Mean	347	1957	23	10	2	12,300,000,000	53,508	8,640,000,000	2,380,000,000	3,826,884	16,307,944	341,821
Median	360	1948	21	5	1	334,000,000	27,815	275,000,000	1,190,000,000	1071	15,689,386	355,305
Maximum	418	2076	46	29	10	113,000,000,000	130,473	75,500,000,000	12,900,000,000	30,360,771	26,786,598	495,683
Minimum	272	1807	−7	2	−1	250,000	19,454	193,500	252,000,000	0	8,827,273	219,327
Std. Dev.	38	66	12	9	3	26,300,000,000	40,160	17,400,000,000	3,080,000,000	8,255,112	5,399,093	76,964
Skewness	−0.4048	0.0252	0.2317	0.7448	1.1955	2.5042	0.6903	2.3418	2.0955	2.1368	0.3432	0.0209
Kurtosis	2.2932	2.3680	3.2326	1.7977	3.0377	8.5307	1.6243	7.8792	6.5000	6.2290	1.9109	1.9782
Jarque-Bera	2.0693	0.5863	0.4816	6.5649	9.5298	102.0677	6.6476	83.8612	54.6592	52.5978	3.0385	1.9173
Probability	0.3553	0.7459	0.7860	0.0375[a]	0.0085[a]	0.0000[a]	0.0360[a]	0.0000[a]	0.0000[a]	0.0000[a]	0.2189	0.3834
Correlation	347	1957	23	10	2	12,300,000,000	53,508	8,640,000,000	2,380,000,000	3,826,884	16,307,944	341,821
ENUS	1											
AGM	0.1420	1										
EGIM	−0.4579	−0.2795	1									
EPTDL	−0.8121	−0.2866	0.8336	1								
FDIN	0.1392	−0.3927	0.3901	0.1809	1							
GDP	−0.6687	−0.5217	0.8882	0.883	0.3257	1						
GHG	−0.3163	−0.4708	0.8281	0.6683	0.5188	0.7622	1					
HFICE	−0.6686	−0.5175	0.8917	0.8856	0.3272	0.9998	0.7678	1				
INA	−0.2143	−0.8340	0.6515	0.5335	0.5676	0.7826	0.7129	0.7812	1			
MCS	−0.6724	−0.4713	0.6926	0.725	0.142	0.8995	0.5265	0.8954	0.6507	1		
POP	−0.3531	−0.8179	0.6831	0.6561	0.5621	0.7973	0.7856	0.7992	0.9255	0.5744	1	
TFP	0.0389	−0.7153	0.3993	0.2929	0.5241	0.4365	0.6024	0.4403	0.7746	0.2030	0.8279	1

[a] Rejection of the Null hypothesis of Normal distribution at 5% significance level.

break". Hence, the study employs Vogelsang and Perron (1998) and Zivot and Andrews (2002) unit root tests for structural breaks. Both tests presented in Table 3 reveals that all the data series are stationary at first difference, therefore, integrated of order one [I(1)]. Zivot and Andrews unit root test in Fig. 2 reveals two prominent regimes after/before/between the break dates.

The structural break test provides a series of information that needs to be examined. Agricultural machinery observed a minimum breakpoint in 2006 due to a decline in the investment in tractors by the Government, however, the trend changed during a regime change.

Industrialization observed a minimum breakpoint in 2006 due to the rise of the agricultural and services sectors' contribution to the GDP therefore much attention was focused on the two. However, industrialization took a rising turn at the commencement of mining crude oil in 2010, quadrupling the share of the industrial sector in Ghana's economic growth (Ackah et al., 2014).

Total fisheries production experienced a minimum breakpoint in 1986 due to a decline of outboard motors that serve as an important feature in canoe fishing. The decline of outboard motors was due to the exponential increase in the price of purchasing, running (price of premix fuel) and maintenance (Wayo Seini, 1995).

The mobile industry began in 1992 in Ghana with over 100% mobile penetration rate, thus, the reason why mobile cellular subscriptions experienced a minimum breakpoint in 1992 (AMGOO, 2014).

Household final consumption expenditure, GDP, and foreign direct investment net inflows observed a minimum breakpoint in 1978 due to the 1978 coup d'état that made Ghana ungovernable. This action led to civil unrest, the dismissal of 1000 public employees, about eighty strike actions taken by civil servants and a declaration of a state of emergency, thus, affecting the country's economic policies including household income (Photius, 2011). In addition, the inflation rate increased to over 92% per year in 1978, affecting both economic growth and foreign direct investment net inflows (Aryeetey et al., 2000).

The total greenhouse gas emissions had a minimum breakpoint in 1998, which was due to the introduction of the forestry development master plan in 1996 that promotes sustainable forest harvesting. The policy made Ghana a net sink due to the high echelons of carbon capture sequestration in the land use, land-use change, and forestry sector. In addition, there was a reduction in energy consumption in 1998 compared to other years, hence, increasing the net greenhouse gas removals (MLNR, 2012).

The net energy import observed a minimum breakpoint in 2007 due to an increase in Ghana's current account deficit from 6.9% in 2006 to 8.6% in 2007, resulting in a trade deficit caused by a higher than expected oil import bill (OECD, 2008). As such, the import cover declined in 2007. Ghana discovered its first indigenous oil and gas in the Jubilee fields in 2007 which saved Ghana US $1000,000 per day on the importation of fuel for thermal power generation (USAID, 2016).

Energy consumption observed a minimum breakpoint in 2000 due to the poor energy sector policies and poor economic state, which turned the country into a highly indebted poor country in 2001. This propelled households to spend relatively small of their expenditure on energy due to high electricity tariffs and prices of petroleum products while salaries and wages remained stagnant (ESMAP, 2006). Electric power transmission and distribution losses experienced a minimum breakpoint in 2000 due to the introduction of a customer base of about 120,000 by the Northern Electricity Department. The distribution system consisted of 8000 km of sub-transmission lines, 22 bulk supply points, 30,000 km distribution networks and 1800 MVA installed transformer capacity which was very efficient leading to a reduction in transmission and distribution losses but however dwindled in the subsequent years (ESMAP, 2006).

The minimum breakpoint in population occurred in 1986 which was due to a decline in fertility rate as a result of the earlier introduction of contraceptives, an increase in under-5 infant mortality rate of 155 per

Table 3
Zivot-Andrews and Vogelsang and Perron Breakpoint Unit Root Test.

Variable	Zivot-Andrews Unit Root Test								Vogelsang and Perron Breakpoint Unit Root Test							
	Level				1st difference				Level				1st difference			
	BD	5% (−4.8/−4.42/−5.08)			BD	5% (−4.8/−4.42/−5.08)			Intercept		Both		Intercept		Both	
	I/T/B	Intercept	Trend	Both	I/T/B	Intercept	Trend	Both	T-Statistic	Prob	T-Statistic	Prob	T-Statistic	Prob	T-Statistic	Prob
AGM	2006/2001/2006	−476.149	−3.425	−402.779	2006/2007/2006	−6.974	−6.756	−10.506	−0.6269	≥0.50	−2.3194	>0.99	−583.7652	<0.01	−576.6685	<0.01
EGIM	2007/2007/2007	−1.249	−3.268	−3.773	2008/2005/2010	−6.462	−6.332	−7.076	−1.5665	>0.99	−1.6612	>0.99	−6.4037	<0.01	−6.3733	<0.01
ENUS	2000/2007/2000	−4.39	−1.994	−3.817	2006/2004/2000	−6.446	−6.412	−8.276	−1.7003	>0.99	−2.1678	>0.99	−7.1421	<0.01	−7.2557	<0.01
EPTDL	2000/1994/2000	−7.62	−3.075	−6.848	2000/2002/2000	−8.253	−8.024	−9.369	−3.092	<0.10	−3.374	<0.10	−10.8199	<0.01	−10.6852	<0.01
FDIN	1978/1984/1977	−3.103	−3.582	−3.887	1987/1994/1987	−6.319	−5.744	−6.283	−1.0768	≥0.50	−2.0194	≥0.50	−5.692	<0.01	−6.6877	<0.01
GDP	1978/1987/1983	−3.157	−4.87	−5.133	1978/1979/1977	−6.896	−7.43	−7.899	−1.4878	≥0.50	−0.7256	>0.90	−5.8905	<0.01	−6.3077	<0.01
GHG	1998/1986/1983	−16.443	−3.14	−4.359	2000/1999/1998	−9.799	−9.494	−10.216	−2.2368	>0.99	−4.2133	<0.025	−6.2801	<0.01	−5.6891	<0.01
HFICE	1978/1987/1998	−3.183	−4.378	−16.374	1978/1979/1977	−7.022	−7.452	−7.722	−1.7283	>0.41	−0.5719	>0.90	−5.9161	<0.01	−6.4708	<0.01
INA	2006/1982/1981	−3.808	−4.194	−4.183	1984/1987/1983	−5.838	−5.361	−6.16	−0.2445	≥0.50	−3.4588	<0.05	−5.453	<0.01	−5.4624	<0.01
MCS	1992/1979/1992	−6.699	−2.07	−13.516	1992/1993/1992	−7.022	−5.897	−7.99	−5.7968	<0.01	−3.5356	<0.10	−32.4316	<0.01	−36.5975	<0.01
POP	1986/1991/1986	−7.423	−8.172	−7.505	1991/1980/1978	−2.454	−4.244	−4.1	−4.8497	>0.10	−3.1525	>0.80	−7.734	<0.01	−8.2349	<0.01
TFP	1986/1999/1996	−4.184	−4.184	−4.558	2000/1987/1988	−8.907	−8.91	−9.046	−4.3873	>0.05	−4.213	>0.25	−9.5847	<0.01	−9.3623	<0.01

NB: I = Intercept, T = Trend, B=Both (Intercept & Trend), BD = Break Date.

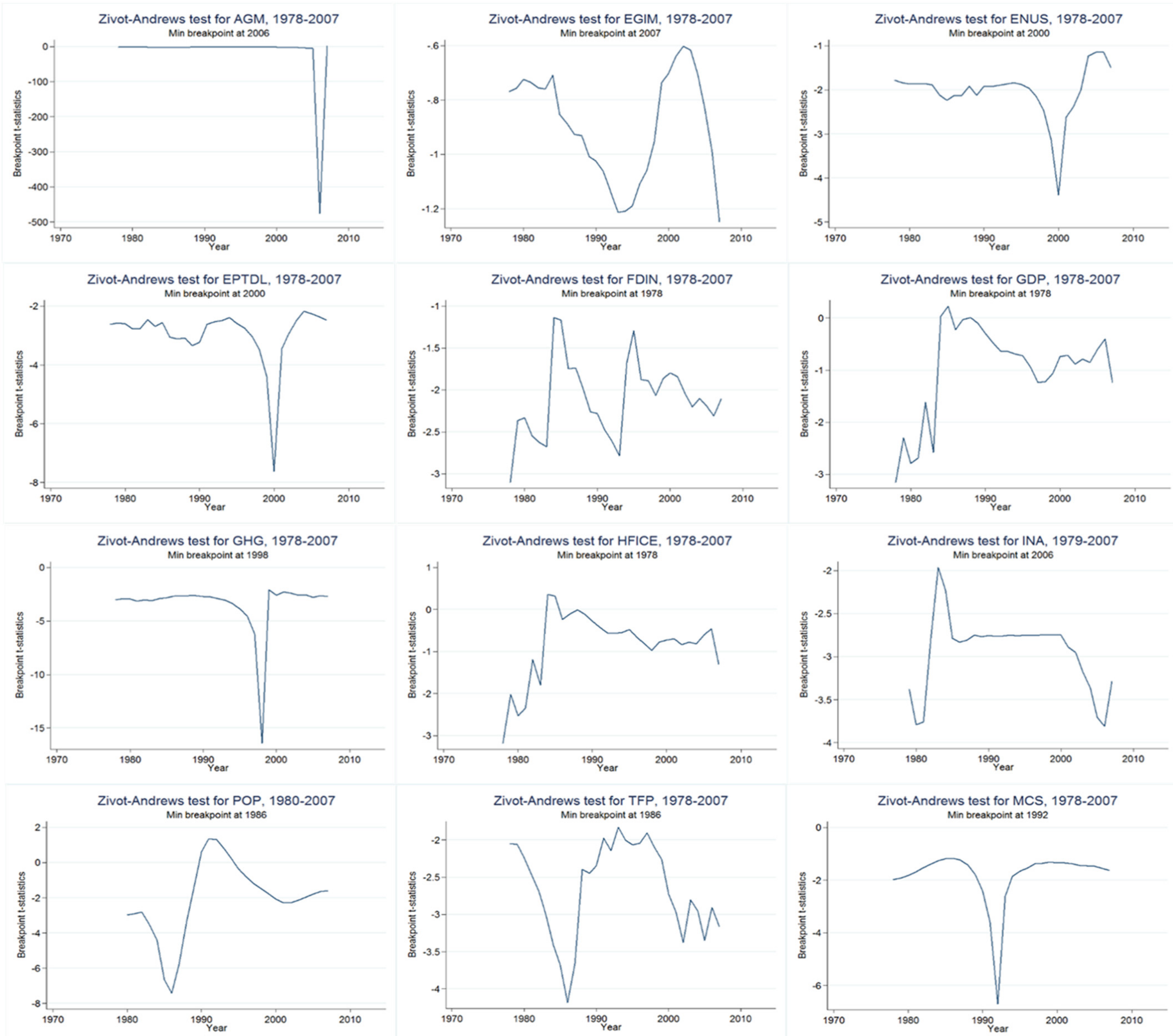

Fig. 2. Structural break using Zivot-Andrews Unit Root Test.

1000 live births and a decline in the proportion of married women (UN, 2001).

The structural breaks have policy implications but requires a methodology (revealed in the subsequent sections) capable of explaining the two regimes in order to prevent speculative assumptions.

4.3. Asymmetric effect of predictors on energy consumption

Table 4 shows the linear regression analysis of the study. The linear regression is employed as a baseline result to examine the impact of the predictor variables on energy consumption without the switching effect. Table 4 reveals that only net energy imports and electric power transmission and distribution losses are significant at 5% level. To test the asymmetric effect of the predictor variables on energy consumption, the study estimates the Markov-switching dynamic regression which considers the switching effect. The results of the Markov-switching dynamic regression in Table 5 shows statistical significance for all the predictor variables. Essentially, the linear regression and the Markov-switching dynamic regression have the same sign (i.e. negative/positive) and significant at 5% level. Table 5 shows that

Table 4
Linear regression analysis.

Source	SS	df	MS	Number of obs	44
				F(11, 32)	15.82
Model	0.4586	11	0.0417	Prob > F	0.0000
Residual	0.0843	32	0.0026	R-squared	0.8447
				Adj R-squared	0.7913
Total	0.5429	43	0.0126	Root MSE	0.0513

ENUS	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
AGM	0.0130	0.0069	1.89	0.0670	−0.0010	0.0270
EGIM	−0.0520	0.0247	−2.11	0.0430	−0.1023	−0.0017
EPTDL	−0.0808	0.0180	−4.49	0.0000	−0.1174	−0.0442
FDIN	0.0353	0.0175	2.02	0.0510	−0.0002	0.0709
GDP	0.1391	0.2666	0.52	0.6060	−0.4040	0.6822
GHG	0.0499	0.0337	1.48	0.1480	−0.0186	0.1185
HFICE	−0.0732	0.2549	−0.29	0.7760	−0.5924	0.4460
INA	0.0503	0.0451	1.11	0.2730	−0.0416	0.1422
MCS	−0.0078	0.0063	−1.23	0.2260	−0.0207	0.0051
POP	−0.9794	0.7216	−1.36	0.1840	−2.4492	0.4905
TFP	0.1014	0.0785	1.29	0.2050	−0.0584	0.2612
_cons	18.1719	10.6136	1.71	0.0970	−3.4474	39.7911

Table 5
Markov-switching dynamic regression.

	Variable	Coef.	Std. Err.	z	P > z
ENUS	AGM	0.0097	0.0024	4.1000	0.0000
	EGIM	−0.0231	0.0086	−2.6900	0.0070
	EPTDL	−0.0815	0.0061	−13.3500	0.0000
	FDIN	0.0347	0.0059	5.8800	0.0000
	GDP	0.2973	0.0917	3.2400	0.0010
	GHG	0.0336	0.0116	2.9000	0.0040
	HFICE	−0.2636	0.0875	−3.0100	0.0030
	INA	0.0310	0.0153	2.0200	0.0430
	MCS	−0.0098	0.0022	−4.5100	0.0000
	POP	−0.4742	0.2412	−1.9700	0.0490
	TFP	0.0541	0.0272	1.9900	0.0470
State 1	_cons	11.4730	3.5443	3.2400	0.0010
State 2	_cons	11.5625	3.5436	3.2600	0.0010
	sigma	0.0175	0.0019		

agricultural machinery, foreign direct investment net inflows, economic growth, total greenhouse gas emissions, industrialization and total fisheries production have a positive effect on energy consumption while net energy imports, electric power transmission, and distribution losses, household final consumption expenditure, mobile cellular subscriptions, and population have a negative effect on energy consumption. In this study, state 1 is classified as "*energy crisis*" with high volatility while state 2 is classified as "*energy boom*" with low volatility. The output in Table 4 shows that energy consumption will grow by 11.6% during the energy boom periods while growth will decline by 0.1% during the period of energy crisis (11.5%). Table 6 presents the post-estimation of Markov-switching dynamic regression. The expected duration and the transition probability of entry into the two states are estimated. The output in Table 6 reveals that 11.6% growth in energy consumption is expected to occur in 4.1 years while energy crisis is expected to last for 3.7 years. Further evidence shows a 73% probability (p11) of remaining in 3.7 years of energy crisis while there is a 75% chance of staying in 4.1 years of energy boom (p22). The probability (p12) of switching from energy crisis to energy boom is 27%, and the probability (p21) of changing from an energy boom to energy crisis is 25%. The predictive power of state 1 and state 2 on energy consumption is examined as a sensitivity analysis presented in Fig. 3. We employ MAPE and R-square as error and predictive power metrics. Fig. 3(a) reveals that state 1 has a MAPE of 0.91% while state 2 has a MAPE of 0.86% (Appendix A). We select state 2 with minimum MAPE to examine its predictive power presented in Fig. 3(b). It is evident that the predictor variables in state 2 explain 81% (i.e. $R^2 = 0.81$) of observed dynamics in Energy consumption.

4.4. Neural network estimation

This section examines the predictive power of the neural network model via a causal relationship between energy consumption, agricultural machinery, foreign direct investment net inflows, economic growth, total greenhouse gas emissions, industrialization, total fisheries production, net energy imports, electric power transmission and distribution losses, household final consumption expenditure, mobile cellular subscriptions and population. Fig. 4 shows the exact input-output diagram of the model that employs one layer. The study employs a TanH activation function [i.e. TanH {(TanH $= e^{2x} - 1/e^{2x} + 1$) where x is a linear combination of the predictors} which is a sigmoid function that converts a value between −1 and 1 (see Appendix A)] at the nodes of the hidden layer. The resultant Predicted ENUS equation using a one-layered feedforward network with three hidden nodes is presented as:

$$PredENUS = 5.5510 + -0.1194* : H1_1 + -0.1140* : H1_2 + 0.3825* : H1_3 \tag{19}$$

where, the output equations based on the hidden layer from the model are expressed as:

$$\begin{aligned} \mathrm{H1}_1 : \mathrm{TanH}(0.5 * (112.3534 + -0.3939* : \mathrm{AGM} + -1.8115* : \mathrm{EGIM} \\ + -0.2193* : \mathrm{EPTDL} + -1.2334* : \mathrm{FDIN} + 0.2788* : \mathrm{GDP} \\ + 1.2323* : \mathrm{GHG} + 0.9370* : \mathrm{HFICE} + 0.5512* : \mathrm{INA} \\ + -0.2972* : \mathrm{MCS} + -3.3136* : \mathrm{POP} + -7.7411* : \mathrm{TFP})) \end{aligned} \tag{20}$$

$$\begin{aligned} \mathrm{H1}_2 : \mathrm{TanH}(0.5 * (145.9786 + -0.0661* : \mathrm{AGM} + -2.2040* : \mathrm{EGIM} \\ + -0.7693* : \mathrm{EPTDL} + 0.1199* : \mathrm{FDIN} + -0.2646* : \mathrm{GDP} \\ + -2.9475* : \mathrm{GHG} + -0.2758* : \mathrm{HFICE} + -1.9081* : \mathrm{INA} \\ + -0.4148* : \mathrm{MCS} + -4.8500* : \mathrm{POP} + 2.2950* : \mathrm{TFP})) \end{aligned} \tag{21}$$

$$\begin{aligned} \mathrm{H1}_3 : \mathrm{TanH}(0.5 * ((-160.7658) + -0.0542* : \mathrm{AGM} + -0.4877* : \mathrm{EGIM} \\ + -0.4435* : \mathrm{EPTDL} + -0.0613* : \mathrm{FDIN} + 0.7052* : \mathrm{GDP} \\ + -0.5345* : \mathrm{GHG} + -0.3905* : \mathrm{HFICE} + 0.2477* : \mathrm{INA} \\ + -0.9188* : \mathrm{MCS} + 10.2696* : \mathrm{POP} + -0.2103* : \mathrm{TFP})) \end{aligned} \tag{22}$$

Thus, $H1_1$, $H1_2$ and $H1_3$ are the hidden nodes from the one-layered feedforward neural network model.

Fig. 5 presents the training and validation plots of the neural network model while the corresponding goodness of fit estimates are displayed in Table 7. Due to the flexibility of the neural network model, there may arise problems related to overfitting data, which will, in turn, predict future observations poorly. This temptation of overfitting is prevented via the application of a "penalty" on the parameters of the model and the assessment of the predictive power of the model using an independent dataset for validation. Fig. 5 reveals evidence of 35 observations for the training set and 9 observations for the validation set. This study employs the K-Fold validation method advantaged in the efficient use of a small sample dataset and produces accurate predictions. The output results in Table 7 shows that the training and validation set predict energy consumption at almost 99% R-Squared value, 0.01 RSME value, 0.01 MAD value, 0.01 SSE value and 0.16% MAPE value (Appendix A). The predictive power and error metrics confirm the relationship between energy consumption and the predictor variables.

4.5. Determinants of energy consumption

To examine the determinants of energy consumption, the study employs the NIPALS regression analysis. NIPALS regression is a powerful multivariate analysis that is superior to other conventional econometric methods in terms of accuracy, predictability and variable projections. The model allows for the imputation of missing data using their means. The NIPALS regression analysis begins with the selection of a viable model using the number of factors available. Appendix B presents a model comparison summary. The output in Appendix B shows that the

Table 6
Post estimation of Markov-switching dynamic regression.

Post estimation	Estimate	Std. Err.	[95% Conf. Interval]	
Expected duration				
State 1	3.7299	1.3439	2.0402	8.1644
State 2	4.0710	1.4814	2.1931	8.9044
Transition probabilities				
p11	0.7319	0.0966	0.5099	0.8775
p12	0.2681	0.0966	0.1225	0.4901
p21	0.2456	0.0894	0.1123	0.4560
p22	0.7544	0.0894	0.5440	0.8877

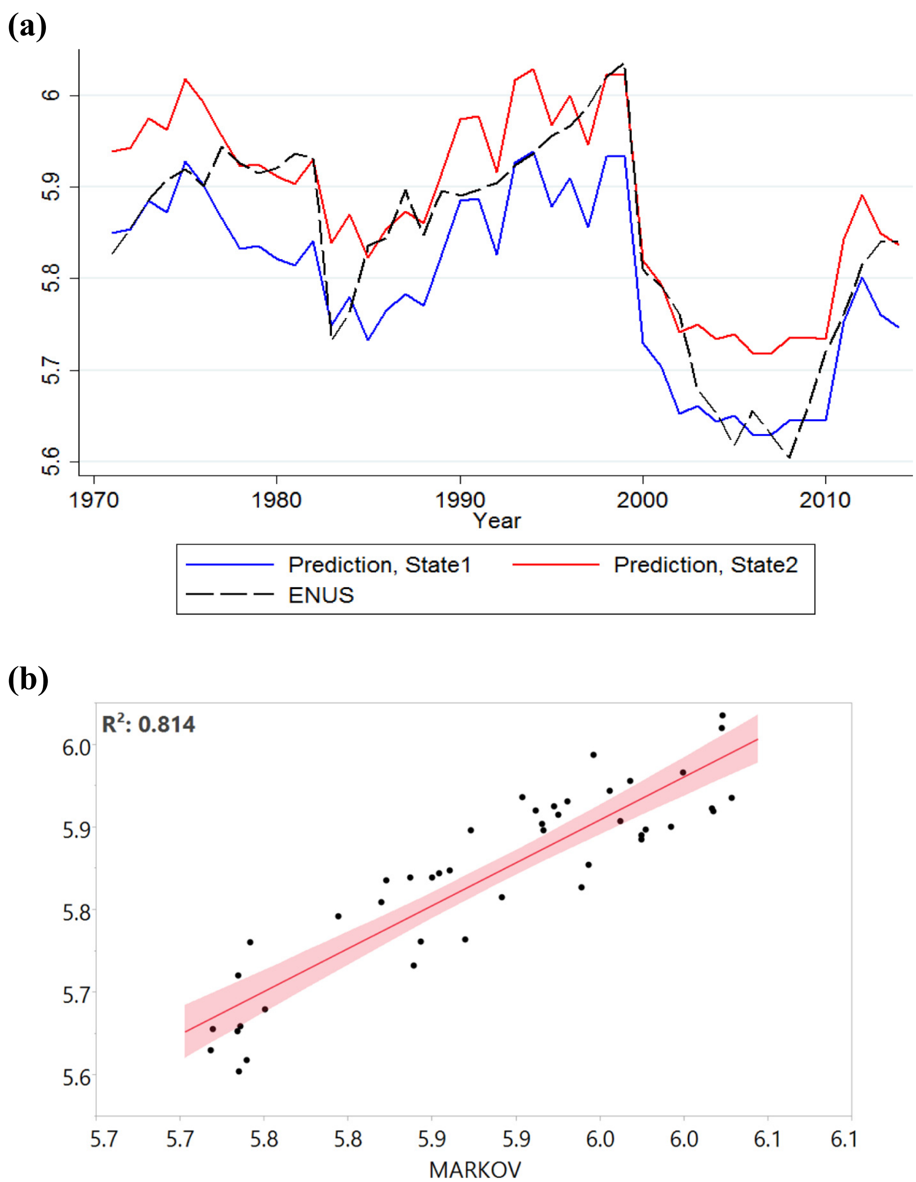

Fig. 3. (a) Prediction of ENUS by states (b) Markov-switching dynamic regression model.

model with the asterisk (*) is superior compared to the others, accordingly, selected for further analysis. The selected model has a corresponding number of factors in Appendix C required for coefficient estimation. Appendix C shows that almost all the variables have VIP greater than or equal to 0.8, a requirement for selecting important variables (Samuel and Owusu, 2017). The variables can be classified into two categories based on their VIP value; EPTDL, EGIM, and TFP are highly important variables (VIP > 1) while the remaining predictor variables are moderately important variable thus, 0.8 ≤ VIP ≤ 1. Now, we estimate the coefficient of the regression analysis using the 11 factors presented in Appendix D and its corresponding output in Appendix B.

The NIPALS estimated coefficients in Table 8 have the same sign as the linear regression (Table 4) and the Markov-switching dynamic regression (Table 5) analysis, hence, confirming the validity of the coefficients in explaining the relationship between the response and the predictor variables. The output in Table 8 reveals that a 1% increase in agricultural machinery, foreign direct investment net inflows, economic growth, total greenhouse gas emissions, industrialization, and total fisheries production increases energy consumption by 0.35%, 0.47%, 5.00%, 0.32%, 0.47%, and 0.21%. In contrast, net energy imports, electric power transmission and distribution losses, household final consumption expenditure, mobile cellular subscriptions, and population decreases energy consumption by 0.30%, 0.65%, 2.62%, 0.49%, and 2.93%. The next step is to examine the independence of the residuals and the predictive power of the NIPALS regression. Appendix E shows a diagnostic plot of the residuals while Fig. 6 depicts the NIPALS Prediction Plot. The residual normal quantile plot shows that the residuals of the model are normally distributed. We examine the prediction error using MAPE. The error metric reveals a MAPE of 0.64% (Appendix A). Fig. 6 shows that the predictor variables can explain about 85% of the dynamics in energy consumption.

The Markov-switching dynamic regression shows that linear regression is incapable of examining the relationship between energy consumption and the predictors in the presence of structural breaks. Using the linear regression as a baseline and the NIPALS regression as a validation method for the study, the Markov-switching dynamic regression showed the asymmetric effect of the predictors on energy consumption. It was evident in Table 5 and Table 8 that agricultural machinery, foreign direct investment net inflows, economic growth, total greenhouse gas emissions, industrialization, and total fisheries production have a positive effect on energy consumption. It is positive in the sense of increasing the demand for energy consumption.

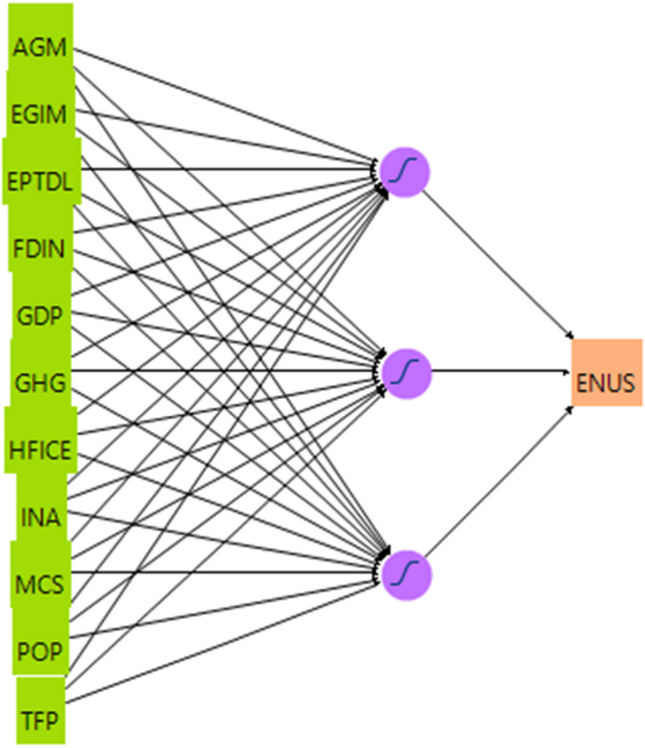

Fig. 4. One-layered feedforward neural network model for energy consumption.

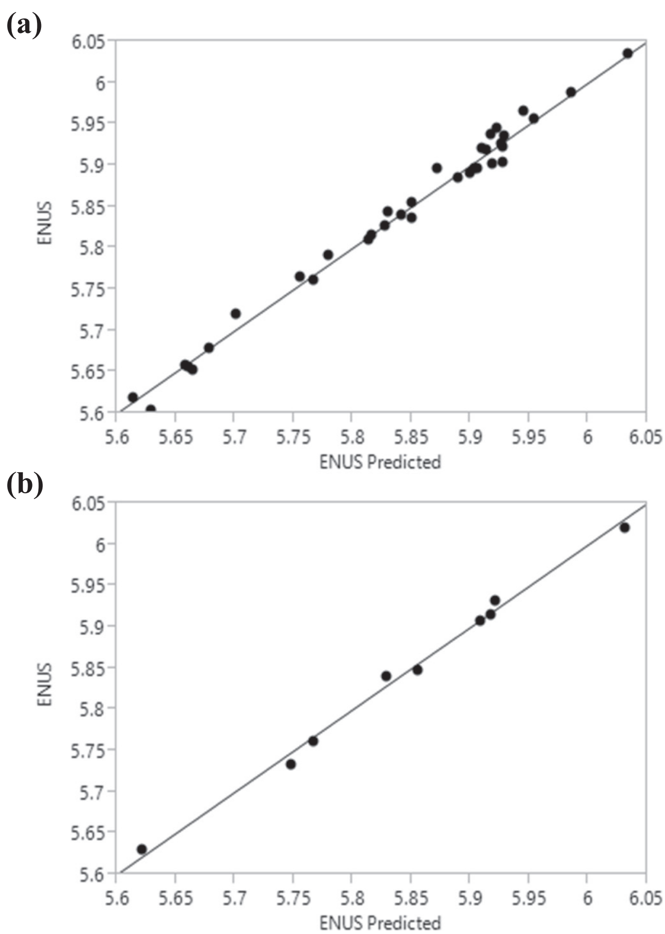

Fig. 5. Model: (a) training and (b) validation.

Table 7
The goodness of fit estimation of the model.

ENUS	Training	Validation
Measures	Value	Value
RSquare	0.9881	0.9931
RMSE	0.0121	0.0093
MAD	0.0093	0.0081
-LogLikelihood	−104.8593	−29.3045
SSE	0.0051	0.0008
Sum Freq	35	9

Agricultural machineries are dependent on fuel for its operations in medium and large-scale agricultural production. Therefore, as large-scale agricultural production enhances, agricultural machineries evolves, hence, increasing energy demand (fossil fuels). Our study is supported by Kuang et al. (2017), they found a relationship between agricultural mechanization and energy consumption in China. Their study concluded that energy consumption and efficient agricultural mechanization are strongly linked with agricultural economic growth.

As of 2010, fisheries production accounted for 7.3% of the agricultural GDP in Ghana (Asumadu and Owusu, 2016a). Thus, Government invests more to boost the sustainable production through the provision of subsidies on premix fuel. Fisheries production impact energy consumption in the sense of premix fuels used to operate outboard motors for canoe fishing. Tyedmers (2004) argues that energy in the form of fuel is used directly in fishing vessels for vessel propulsion. In large-scale fishing, high-intensity lamp batteries, onboard processing, automated jigging machines, refrigeration, freezing, vessel construction, and maintenance are all powered by diesel-fueled generators, therefore, increasing energy consumption (Tyedmers, 2004).

Contrary to the work of Adom (2015) that suggests a negative effect of Foreign direct investment net inflows on energy intensity in South Africa, Sadorsky (2010) confirms our results, thus, a positive effect of Foreign direct investment net inflows on energy consumption (Sadorsky, 2010). Foreign direct investment net inflows play a critical role in Ghana's energy consumption. Legislation and structural frameworks that provide an enabling environment to attract foreign investors give Ghana a comparative advantage over other Sub-Saharan African countries in terms of foreign investments (Sarkodie and Strezov, 2019). The multi-party democracy system, the rule of law, good governance (i.e. “first country to be reviewed under the Africa Peer Review Mechanism of NEPAD”.), peaceful socio-political environment, outstanding hospitality and personal security, the availability of export free zone territory, access to tariff-free exports to the USA via the Africa Growth and Opportunity Act, the vast ongoing oil exploration, endowed natural resources, and among others entice foreign direct investment to the energy sector (CGA, 2017). For example, a compact was signed in 2014 between Ghana and the Millennium Challenge

Table 8
Model coefficients for centred and scaled data.

Coefficient	ENUS	Plot
Intercept	0.0000	
AGM	0.3579	
EGIM	−0.3045	
EPTDL	−0.6534	
FDIN	0.4725	
GDP	5.0147	
GHG	0.3252	
HFICE	−2.6233	
INA	0.4684	
MCS	−0.4919	
POP	−2.9376	
TFP	0.2107	

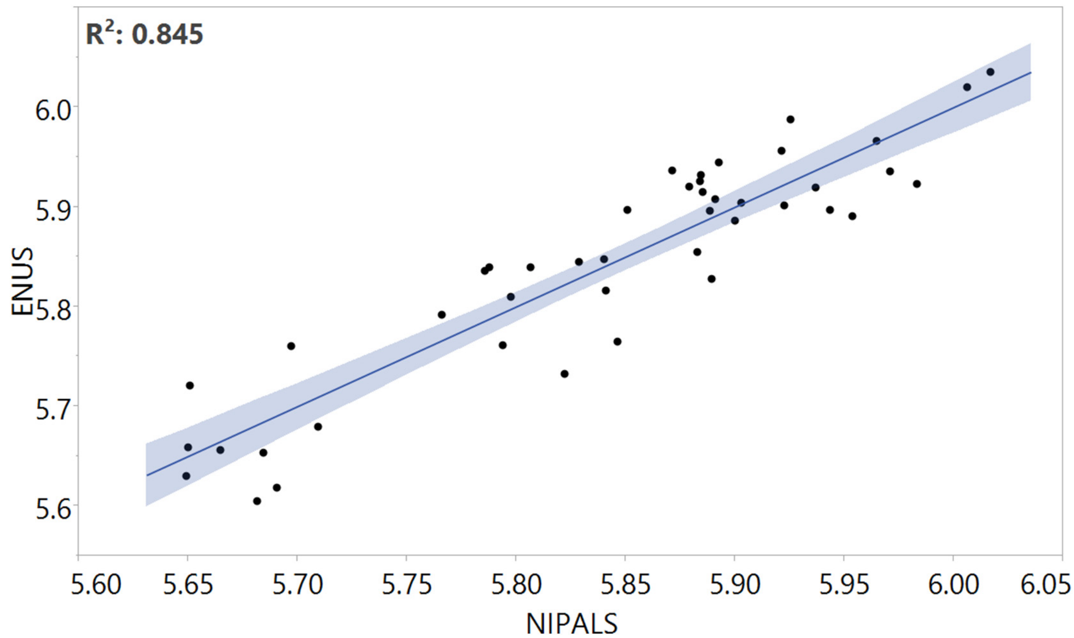

Fig. 6. NIPALS Prediction Plot.

Corporation for an investment of US$ 498.2 million to enable the renovation of Ghana's energy sector (i.e. electricity production, distribution, and accessibility to clean energy) and to motivate foreign and private investment (USAID, 2017). Foreign direct investment net inflows mediate in either the expansion of Ghana's energy sector or widening the energy demand, which increases energy consumption. Sadorsky (2010) argues that financial development is a sign of prosperity and economic growth that strengthens customer and business confidence thereby increasing the economic demand for energy-intensive goods.

Economic growth has a positive effect on energy consumption with corresponding positive foreign direct investment net inflows. Developed countries with sustained and high economic growth rates can institute policies and measures that enable access to constant electricity while developing and least developing countries stand a risk of energy supply interruptions due to inconsistent economic growth, which Ghana is not an exception (DiSano, 2002). The positive effect of the total greenhouse gas emissions on energy consumption means that environmental policies and renewable energy policies are put into effect to repeal and replace fossil fuel energy sources with green energy while meeting the energy demand.

The positive effect of industrialization means it stimulates energy consumption. Ghana's peak demand has been increasing due to loads emanating from the industrial and commercial sectors. The upstream activities of Ghana's petroleum sector involve the production and refining of crude oil and other petroleum products to meet the needs of the industrial sector. For example, there has been a development of the West Africa gas pipeline to feed industries with fuel (CGA, 2017; Owusu and Sarkodie, 2016).

In contrast, Table 5 and Table 8 revealed a negative effect of energy imports, electric power transmission, and distribution losses, household final consumption expenditure, mobile cellular subscriptions, and population on energy consumption. The study expected a positive effect of energy imports, household final consumption expenditure, mobile cellular subscriptions, and population on energy consumption. However, the results proved otherwise, but surprisingly, all the three regressions have the same sign which means the models have no misspecification problem. Theoretically, as energy imports, household final consumption expenditure, population, and mobile cellular subscriptions increases, it is expected that energy demand which translates into consumption will increase. As household consumption expenditure increases, members of the household are able to afford energy-intensive goods and services thus, consuming more energy. However, the negative effect of household consumption expenditure maybe due to energy efficiency and conservation practices such as using green energy technologies and services that reduce energy consumption. Increasing population becomes burdensome on the peak energy demand, thus, increasing energy demand and consumption. Social media like Facebook, WhatsApp, Snap Chat, Instagram and among others propel the use of mobile phones in Ghana. The use of 4G, 3G, and wireless networks in mobile phones drain more battery compared to GSM, as such, the frequency of charging mobile phones increases, thus, affecting electricity demand. It is reported that base stations in cellular networks account for over 50% of energy consumption in mobile phones (Han and Ansari, 2013). It is in this regard that mobile cellular subscription is an important factor in assessing the determinants of energy consumption. Increasing levels of electric power transmission and distribution losses reduce energy consumption, which affects energy efficiency and conservation.

5. Conclusion

This study examined the asymmetric behavior of energy consumption by assessing Ghana's energy sector dynamics. Using a time series data from 1971 to 2014, the study employed Markov-switching dynamic regression to examine the asymmetric effect, NIPALS regression to examine the determinants of energy consumption and neural network analysis for prediction.

Using Vogelsang and Perron, and Zivot and Andrews unit root tests for structural breaks, the study revealed some historical information that has policy implications but required a methodology that could explain the two regimes exhibited in the structural break plots. While the linear regression used as a baseline of the study had limitations, the Markov-switching dynamic regression revealed the presence of asymmetric effect in the presence of structural breaks.

It was evident in both Markov-switching and NIPALS regression that agricultural machinery, foreign direct investment net inflows, economic growth, total greenhouse gas emissions, industrialization, and total fisheries production have a significant positive effect on energy consumption. However, both models showed a significant negative effect of energy imports, electric power transmission, and distribution losses, household final consumption expenditure, mobile cellular subscriptions, and population on energy consumption.

The study revealed that energy consumption evolves in two different states (energy boom and energy scarcity) by transitioning over a finite set of unobserved states. Energy consumption is expected to grow by 11.6% during the energy boom periods while growth will decline by 0.1% during energy crisis (11.5%). The expected duration and the transition probability of entry into the two states show that 11.6% growth in energy consumption is expected to occur in 4.1 years while energy crisis is expected to last for 3.7 years. There is 73% probability of staying in energy crisis for 3.7 years while the chance of staying in 4.1 years of energy boom is 75%. The probability of switching from energy crisis to energy boom is 27%, while the probability of changing from an energy boom to energy crisis is 25%.

The NIPALS regression revealed unobserved or unreported factors like electric power transmission, and distribution losses, and mobile cellular subscriptions underpinning energy crisis. There was evidence of continuous shift in the regression from agricultural machinery, foreign direct investment net inflows, economic growth, total greenhouse gas emissions, industrialization, total fisheries production, net energy imports, electric power transmission and distribution losses, household final consumption expenditure, mobile cellular subscriptions, and population to energy consumption at a known point.

Even though the neural network is disadvantaged in terms of interpretability yet revealed an accurate prediction of energy consumption compared to the Markov-switching dynamic and the NIPALS regression models. The neural network model suggests a 99% relationship between energy consumption and the predictors.

As a policy implication, there is the need for improved and sustainable agricultural mechanization systems in Ghana to enhance the efficient use of energy while increasing agricultural productivity. As foreign direct investment net inflows propel technological advancement and the development of green energy and energy efficiency, is essential for the Government of Ghana to improve the renewable energy policy that will provide more incentives and bolster foreign and private investment into the energy sector. There is the need for sustained and high economic growth rates in Ghana through the institution of financial policies and measures that increases financial development, which will help the development and access to constant electricity thereby increasing productivity.

Future research should aim at expanding the scope of the study to include the role of research development and income inequality on energy consumption.

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Declaration

There is no conflict of interest.

Appendices A–E. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.10.147.

References

Ackah, C., Adjasi, C., Turkson, F., 2014. Scoping Study on the Evolution of Industry in Ghana. WIDER Working Paper.

Adom, P.K., 2015. Determinants of energy intensity in South Africa: testing for structural effects in parameters. Energy 89, 334–346. https://doi.org/10.1016/j.energy.2015.05.125.

Ahmed, K., Shahbaz, M., Kyophilavong, P., 2016. Revisiting the emissions-energy-trade nexus: evidence from the newly industrializing countries. Environ. Sci. Pollut. Res. 23, 7676–7691.

AMGOO, 2014. Mobile industry in Africa: the changing face of mobile in Ghana. Retrieved from. http://www.amgoo.com/blog/mobile-industry-in-africa-the-changing-face-of-mobile-in-ghana.

Aryeetey, E., Harrigan, J., Nissanke, M., 2000. Economic Reforms in Ghana: The Miracle and the Mirage. Africa World Press.

Asumadu, S.S., Owusu, P.A., 2016a. The relationship between carbon dioxide and agriculture in Ghana: a comparison of VECM and ARDL model. Environ. Sci. Pollut. Res. Int. 23, 10968–10982. https://doi.org/10.1007/s11356-016-6252-x.

Asumadu, S.S., Owusu, P.A., 2016b. Carbon dioxide emissions, GDP, energy use, and population growth: a multivariate and causality analysis for Ghana, 1971-2013. Environ. Sci. Pollut. Res. 23, 13508–13520. https://doi.org/10.1007/s11356-016-6511-x.

CGA, 2017. Investing in Ghana's energy sector. Retrieved from. http://www.chinagoabroad.com/en/guide/investing-in-ghana-s-energy-sector.

Chang, S.-C., 2015. Effects of financial developments and income on energy consumption. Int. Rev. Econ. Financ. 35, 28–44.

Destek, M.A., Sarkodie, S.A., 2019. Investigation of environmental Kuznets curve for ecological footprint: the role of energy and financial development. Sci. Total Environ. 650, 2483–2489. https://doi.org/10.1016/j.scitotenv.2018.10.017.

DiSano, J., 2002. Indicators of Sustainable Development: Guidelines and Methodologies. United Nations Department of Economic and Social Affairs, New York.

ESMAP, 2006. Ghana: sector reform and the pattern of the poor, energy use and supply. Retrieved from. http://documents.worldbank.org/curated/en/421071468252576846/pdf/435860WP0Box0327368B0PUBLIC1.pdf.

Faucheux, S., Nicolaï, I., 2011. IT for green and green IT: a proposed typology of eco-innovation. Ecol. Econ. 70, 2020–2027.

Goldfeld, S.M., Quandt, R.E., 1973. A Markov model for switching regressions. J. Econ. 1, 3–15.

Hamdi, H., Sbia, R., Shahbaz, M., 2014. The nexus between electricity consumption and economic growth in Bahrain. Econ. Model. 38, 227–237.

Hamilton, J.D., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica: Journal of the Econometric Society 357–384.

Han, T., Ansari, N., 2013. On optimizing green energy utilization for cellular networks with hybrid energy supplies. IEEE Trans. Wirel. Commun. 12, 3872–3882. https://doi.org/10.1109/TCOMM.2013.051313.121249.

Inglesi-Lotz, R., Pouris, A., 2016. On the causality and determinants of energy and electricity demand in South Africa: a review. Energ Source Part B 11, 626–636.

Jones, B.D., Kim, C.-J., Startz, R., 2010. Does congress realign or smoothly adjust? A discrete switching model of congressional partisan regimes. Statistical Methodology 7, 254–276.

Kuang, Z., Yanbin, Q., Xin, D., 2017. Linking between agricultural mechanization, energy consumption and economic growth. Journal of Agricultural Mechanization Research 3, 002.

Li, W., Ou, Q., Chen, Y., 2014. Decomposition of China's CO_2 emissions from agriculture utilizing an improved Kaya identity. Environ. Sci. Pollut. Res. Int. 21, 13000–13006. https://doi.org/10.1007/s11356-014-3250-8.

Martínez-Beneito, M.A., Conesa, D., López-Quílez, A., López-Maside, A., 2008. Bayesian Markov switching models for the early detection of influenza epidemics. Stat. Med. 27, 4455–4468.

MLNR, G, 2012. Climate Investment Funds Forest Investment Program.

Mohiuddin, O., Sarkodie, S.A., Obaidullah, M., 2016. The relationship between carbon dioxide emissions, energy consumption, and GDP: a recent evidence from Pakistan. Cogent Eng. 3, 1210491. https://doi.org/10.1080/23311916.2016.1210491.

Moyer, J.D., Hughes, B.B., 2012. ICTs: do they contribute to increased carbon emissions? Technol. Forecast. Soc. Chang. 79, 919–931.

OECD, 2008. Ghana. Retrieved from. https://www.oecd.org/dev/emea/40577770.pdf.

Owusu, P., Asumadu, S.S., 2016. A review of renewable energy sources, sustainability issues and climate change mitigation. Cogent Eng. 3, 1167990. https://doi.org/10.1080/23311916.2016.1167990.

Owusu, P.A., Samuel, S.A., 2016. Multivariate co-integration analysis of the Kaya factors in Ghana. Environ. Sci. Pollut. Res. Int. 23, 9934–9943. https://doi.org/10.1007/s11356-016-6245-9.

Owusu, P., Sarkodie, S., 2016. A review of Ghana's energy sector national energy statistics and policy framework. Cogent Eng. 3, 1155274. https://doi.org/10.1080/23311916.2016.1155274.

Perron, P., 1989. The great crash, the oil price shock, and the unit root hypothesis. Econometrica: Journal of the Econometric Society 1361–1401.

Photius, 2011. Ghana the Akuffo Coup, 1978. Retrieved from. http://www.photius.com/countries/ghana/national_security/ghana_national_security_the_akuffo_coup_197~150.html.

Quandt, R.E., 1972. A new approach to estimating switching regressions. J. Am. Stat. Assoc. 67, 306–310.

Sadorsky, P., 2010. The impact of financial development on energy consumption in emerging economies. Energy Policy 38, 2528–2535. https://doi.org/10.1016/j.enpol.2009.12.048.

Salahuddin, M., Alam, K., 2015. Internet usage, electricity consumption and economic growth in Australia: a time series evidence. Telematics Inform. 32, 862–878.

Salahuddin, M., Alam, K., 2016. Information and communication technology, electricity consumption and economic growth in OECD countries: a panel data analysis. Int. J. Electr. Power 76, 185–193.

Samuel, A.S., Owusu, P.A., 2017. The impact of energy, agriculture, macroeconomic and human-induced indicators on environmental pollution: evidence from Ghana. Environ. Sci. Pollut. Res. Int. 24, 6622–6633. https://doi.org/10.1007/s11356-016-8321-6.

Sarkodie, S.A., Adom, P.K., 2018. Determinants of energy consumption in Kenya: a NIPALS approach. Energy 159, 696–705. https://doi.org/10.1016/j.energy.2018.06.195.

Sarkodie, S.A., Owusu, P.A., 2016. Carbon dioxide emissions, GDP per capita, industrialization and population: an evidence from Rwanda. Environ. Eng. Res. 22, 116–124. https://doi.org/10.4491/eer.2016.097.

Sarkodie, S.A., Strezov, V., 2018. Assessment of contribution of Australia's energy production to CO_2 emissions and environmental degradation using statistical dynamic approach. Sci. Total Environ. 639, 888–899. https://doi.org/10.1016/j.scitotenv.2018.05.204.

Sarkodie, S.A., Strezov, V., 2019. Effect of foreign direct investments, economic development and energy consumption on greenhouse gas emissions in developing countries. Sci. Total Environ. 646, 862–871. https://doi.org/10.1016/j.scitotenv.2018.07.365.

Tyedmers, P., 2004. Fisheries and energy use. Encyclopedia of Energy 2, 683–693.

UN, 2001. Africa, in sub-Saharan, workshop on prospects for fertility decline in high fertility countries. Retrieved from. http://www.un.org/esa/population/publications/prospectsdecline/makinwa.pdf.

United Nations, 2015. Sustainable development goals. Retrieved from. https://sustainabledevelopment.un.org/?menu=1300.

USAID, 2016. Ushering in Ghana's gas revolution. Retrieved from. https://www.usaid.gov/power-africa/newsletter/june2016/ushering-in-ghana.

USAID, 2017. Power Africa: investment brief for the electricity sector in Ghana. Retrieved from. https://www.usaid.gov/sites/default/files/documents/1860/Ghana%20_IG_2015_05_03.pdf.

Van Heddeghem, W., Lambert, S., Lannoo, B., Colle, D., Pickavet, M., Demeester, P., 2014. Trends in worldwide ICT electricity consumption from 2007 to 2012. Comput. Commun. 50, 64–76.

Vogelsang, T.J., Perron, P., 1998. Additional tests for a unit root allowing for a break in the trend function at an unknown time. Int. Econ. Rev. 1073–1100.

Wayo Seini, A., 1995. Economics of Marine Canoe Fisheries in Ghana.

Wold, S., Sjöström, M., Eriksson, L., 2001. PLS-regression: a basic tool of chemometrics. Chemom. Intell. Lab. Syst. 58, 109–130.

World Bank, 2016. World development indicators. Retrieved from. http://data.worldbank.org/country.

Zhang, C., Lin, Y., 2012. Panel estimation for urbanization, energy consumption and CO_2 emissions: a regional analysis in China. Energy Policy 49, 488–498.

Zhu, H., Su, X., You, W., Ren, Y., 2017. Asymmetric effects of oil price shocks on stock returns: evidence from a two-stage Markov regime-switching approach. Appl. Econ. 49, 2491–2507.

Zivot, E., Andrews, D.W.K., 2002. Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. J. Bus. Econ. Stat. 20, 25–44.

Zou, X.X., Li, Y., Li, K., Cremades, R., Gao, Q.Z., Wan, Y.F., Qin, X.B., 2015. Greenhouse gas emissions from agricultural irrigation in China. Mitig. Adapt. Strateg. Glob. Chang. 20, 295–315. https://doi.org/10.1007/s11027-013-9492-9.