Environ Sci Pollut Res (2017) 24:6622–6633
DOI 10.1007/s11356-016-8321-6

RESEARCH ARTICLE

The impact of energy, agriculture, macroeconomic and human-induced indicators on environmental pollution: evidence from Ghana

Samuel Asumadu-Sarkodie[1] · Phebe Asantewaa Owusu[1]

Received: 7 July 2016 / Accepted: 21 December 2016 / Published online: 12 January 2017

Abstract In this study, the impact of energy, agriculture, macroeconomic and human-induced indicators on environmental pollution from 1971 to 2011 is investigated using the statistically inspired modification of partial least squares (SIMPLS) regression model. There was evidence of a linear relationship between energy, agriculture, macroeconomic and human-induced indicators and carbon dioxide emissions. Evidence from the SIMPLS regression shows that a 1% increase in crop production index will reduce carbon dioxide emissions by 0.71%. Economic growth increased by 1% will reduce carbon dioxide emissions by 0.46%, which means that an increase in Ghana's economic growth may lead to a reduction in environmental pollution. The increase in electricity production from hydroelectric sources by 1% will reduce carbon dioxide emissions by 0.30%; thus, increasing renewable energy sources in Ghana's energy portfolio will help mitigate carbon dioxide emissions. Increasing enteric emissions by 1% will increase carbon dioxide emissions by 4.22%, and a 1% increase in the nitrogen content of manure management will increase carbon dioxide emissions by 6.69%. The SIMPLS regression forecasting exhibited a 5% MAPE from the prediction of carbon dioxide emissions.

Keywords SIMPLS · Energy economics · Econometrics · Carbon dioxide emissions · Ghana

Responsible editor: Philippe Garrigues

✉ Samuel Asumadu-Sarkodie
asumadusarkodiesamuel@yahoo.com

[1] Sustainable Environment and Energy Systems, Middle East Technical University, Northern Cyprus Campus, Guzelyurt, Turkey

Introduction

Ghana is ranked 140th in the Human Development Report as the only West African country with a medium human development, corresponding to a human development index of 0.579. With a 26.4 million population, almost 31% of the population are in multidimensional poverty, while 12% are in severe multidimensional poverty. In 2011, Ghana achieved a middle-income status of US$1000 per capita as part of the economic growth and poverty reduction agenda by the Government of Ghana. Nonetheless, Ghana has experienced a decline in its annual gross domestic product (GDP) growth. The economic woes worsened in 2014 as the country expressed one of the highest macroeconomic challenges reflected by rising inflation rates and raising public resources to generate domestic revenues for sustainable developmental needs (Asumadu-Sarkodie and Owusu 2016f). The worsened economy has been attributed to low shedding, power outages and inadequate energy supply to meet the growing energy demand. This outcome has affected industrial growth and reduced the labour force leading to a lowered economic growth. The inadequate energy supply is due to variability in rainfall patterns to supply Ghana's Akosombo and Bui dams with the required fuel (water) for hydroelectric power generation. As a result, Ghana's energy sector has incorporated thermal power generation to the energy portfolio to boost the generation capacity (Asumadu-Sarkodie and Owusu 2016a). However, the use of diesel and natural gas as the fuel for the thermal power generation and the overdependence on woodfuel especially firewood and charcoal for cooking and heating purposes by a majority of Ghanaians underpin carbon dioxide emissions.

Agriculture and forestry remain as the backbone of Ghana's growing economy. The former constitutes 43% of the GDP, 50% of export earnings and 70% of total employment (Asumadu-Sarkodie and Owusu 2016c), while the latter accounts for 6%

of the total GDP, 11% of export earnings, and employs 100,000 people in the labour force (FAO 2016). Climate change vulnerability is sensitive to poor communities and economies that depend on climate-sensitive resources like agriculture (IPCC 2015). As a result of climate change and its impacts, farmers in Ghana are purportedly experiencing the signs of the erratic rainfall patterns, the long periods of Harmattan (hot-dry season) and desertification (Akon-Yamga et al. 2011).

Climate change has gained global prominence as a result of its long-term effect on the globe. As a result, climate change mitigation through a sustainable global action deems essential to limit the rising levels of greenhouse gas emissions (Asumadu-Sarkodie and Owusu 2016d; Owusu and Asumadu-Sarkodie 2016a). This global effort has propelled a lot of research interest in environmental, energy and agricultural sustainability (Mohiuddin et al. 2016; Owusu and Asumadu-Sarkodie 2016b; Asumadu-Sarkodie and Owusu 2016g). This paradigm shift in scientific research has increased the interest in using historical data to predict and/or explain the causal effect between response and predictor variables.

According to the Notre Dame Global Adaptation Index (ND-GAIN), Ghana is ranked 108th out of 180 countries performing poorer compared to 2013 (107th) and 2012 (105th), 83rd least ready country and the 59th most vulnerable country. The score means that Ghana is a high vulnerable country in the effort to respond effectively to climate change but has a high readiness, thus a high spirit of urgency and practical steps to employ adaptation options in the effort to mitigate climate change and its impact (ND-GAIN 2014). Against the backdrop, it is essential to examine the impact of energy, agriculture, macroeconomic and human-induced indicators on environmental pollution in Ghana to ascertain the current state of environmental pollution and provide scientific interpretation of the urgency in the efforts towards climate change mitigation.

The remainder of the study comprises of "Literature review", "Methodology", "Results and discussion", and "Conclusion and policy recommendations" sections.

Literature review

Several studies have employed modern econometric techniques such as Engle-Granger's method of cointegration (Engle and Granger 1987); Johansen's method of cointegration (Johansen 1995); Maximum Entropy Bootstrap Method (MEBM); Dynamic fixed effect model (DFE); Fully Modified Ordinary Least Squares (FMOLS); Dynamic Ordinary Least Squares (DOLS); Dynamic Panel Data (DPD); Generalized Method of Moments (GMM); Generalized Estimating Equations (GEE); Generalized Least Squares (GLS); Least Squares (LS); Two-Stage Least Squares (TSLS); Limited Information Maximum Likelihood (LIML); Autoregressive Conditional Heteroskedasticity (ARCH); Binary Choice (Logit, Probit, Extreme Value); Ordered Choice, Censored or Truncated Data (including Tobit); Stepwise Least Squares (STEPLS); Robust Least Squares (ROBUSTLS); Heckman Selection (Generalized Tobit); Least Squares with Breakpoints (BREAKLS); Threshold Regression; Quantile Regression (QREG); Switching Regression (SWITCHREG); Vector Autoregression (VAR); Vector Error Correction Model (VECM); and Autoregressive Distributed Lag (ARDL) to examine the causal relationship between variables in a time series or panel data different disciplines. However, multicollinearity among study variables is problematic in the aforementioned models.

Two strands of studies are analysed in the study. The first strand of existing literature estimates the causal nexus between carbon dioxide emissions and GDP; carbon dioxide emissions and energy-intensity/consumption/production; or a combination of carbon dioxide emissions, energy consumption, GDP and/or population (Acaravci and Ozturk 2010; Apergis and Payne 2011; Asumadu-Sarkodie and Owusu 2016f; Gul et al. 2015; Huang et al. 2008; Jammazi and Aloui 2015; Lozano and Gutiérrez 2008; Ozturk and Acaravci 2010; Qureshi et al. 2016; Remuzgo and Sarabia 2015; Soytas and Sari 2009; Zhang and Cheng 2009). Lozano and Gutiérrez (2008) examined the causal relationship between GDP, CO_2 emissions, energy consumption and population in the USA using a non-parametric frontier method which found evidence of steady efficiency increase in the average of the modelled variables for the estimated period. Gul et al. (2015) examined the relationship between energy consumption and carbon dioxide emissions in Malaysia with a data spanning from 1975 to 2013 by using the maximum entropy bootstrap method (MEBM). Their study found evidence of a unidirectional causality running from energy consumption to CO_2 emissions. Qureshi et al. (2016) examined the relationship between energy crisis, GHG emissions and GDP for the Caribbean, Europe, Asia, Africa and Latin America with a panel data spanning from 1975 to 2012 by employing Johansen's method of cointegration and variance decomposition. Their study found evidence of a negative significant relationship between electricity access and power shortage in certain regions of Europe and Asia. Ozturk and Acaravci (2011) examined the relationship between electricity consumption and economic growth in 11 Middle East and North Africa countries with a data spanning from 1971 to 2006 by employing the ARDL bounds testing method which showed no evidence of long-run equilibrium relationship for Iran, Morocco and Syria. Their study found evidence of long-run equilibrium relationship in Egypt, Oman, Israel and Saudi Arabia. The overall evidence of the seven Middle East and North Africa countries showed no evidence of long-run equilibrium relationship. Asumadu-Sarkodie and Owusu (2016f) examined the multivariate causality analysis of the Kaya factors in Ghana by taking into consideration the total primary energy consumption, GDP, carbon dioxide emissions and population with a data spanning from 1980 to 2012 using the vector error correction model. Evidence from their study showed a long-run causality from the population, GDP and energy consumption to carbon dioxide and a bidirectional causality from CO_2 emissions to energy consumption.

The second strand of existing literature estimates the causal nexus between carbon dioxide emissions, energy consumption, GDP and/or population by adding more variables like; foreign investments, industrialization, trade, urbanization, financial development, etc. (Ben Abdallah et al. 2013; Cerdeira Bento and Moutinho 2016; Rafindadi and Ozturk 2015; Salahuddin et al. 2015; Seker et al. 2015; Shahbaz et al. 2015; Shahbaz et al. 2012; Tiwari et al. 2013). Shahbaz et al. (2015) examined the relationship between energy consumption from road transportation, transport sector value added, fuel prices and CO_2 emissions in Tunisia with a data spanning from 1980 to 2012 by employing the ARDL bounds testing method in the presence of structural breaks which showed an evidence of a long-run equilibrium relationship. Their study found evidence of a bidirectional causality between energy consumption and CO_2 emissions, while fuel prices exhibit a unidirectional causality on energy consumption, road infrastructure, CO_2 emissions and transport sector value added. Ben Abdallah et al. (2013) examined the relationship between energy consumption from road transportation, transport sector value added, fuel prices and CO_2 emissions in Tunisia with a data spanning from 1980 to 2010 by employing the Johansen's method of cointegration and Granger causality test which showed an evidence of a long-run equilibrium relationship. Their study refuted the validity of the environmental Kuznets curve hypothesis and found an evidence of unidirectional causality running from fuel price to energy consumption from road transportation. Cerdeira Bento and Moutinho (2016) examined the relationship between CO_2 emissions per capita, non-renewable electricity production per capita, renewable electricity production per capita, GDP per capita and international trade with a data spanning from 1960 to 2011 in Italy by employing the ARDL bounds testing method in the presence of structural breaks which showed an evidence of a long-run equilibrium relationship. Their study confirmed the validity of the environmental Kuznets curve hypothesis and found an evidence of unidirectional causality running from GDP per capita to renewable electricity production per capita. Salahuddin et al. (2015) examined the relationship between CO_2 emissions, electricity consumption, economic growth and foreign direct investment with a data spanning from 1980 to 2012 in the Gulf Cooperation Council by employing DOLS, FMOLS and DFE methods which showed an evidence of a long-run equilibrium relationship. Their study found evidence of unidirectional causality running from electricity consumption to CO_2 emissions and a bidirectional causality between economic growth and CO_2 emissions.

Spurious regression occurs due to multicollinearity problems among study variables in a model. Hence, informative variables that are essential in explaining a specific response are dropped. Multicollinearity problems have been reported to exist when analysing variables that include environmental pollution, energy consumption and economic growth (Asumadu-Sarkodie and Owusu 2016b; Asumadu-Sarkodie and Owusu 2016g). As a result of multicollinearity problems (thus, the inability for some econometric models like VAR, VECM and ARDL to estimate coefficients per equation due to insufficient observations and the inability to estimate large number of candidate models due to the large number of regressors or the maximum number of lags used in a model), many studies employ few predictor variables which may not be informative in explaining a response variable(s). Contrary to the aforementioned econometric models, the partial least squares regression is able to estimate the relationship between variables that exhibit strong multicollinearity, have the maximum number of lags and have more or an equal number of variable observations than the predictor variables. The partial least squares regression analysis has been employed in previous studies outside the scope of the study (Asumadu-Sarkodie and Owusu 2016e; Ceglar et al. 2016; Mehmood et al. 2012; Xu et al. 2012) and has been labelled as a flexible method for multivariate analysis. Against the backdrop, the study explores the worth of estimating the impact of energy, agriculture, macroeconomic and human-induced indicators on environmental pollution in Ghana with 21 variables using the statistically inspired modification of partial least squares (SIMPLS). The study contributes to the global debate on climate change through the use of a versatile methodology and more informative variables that are essential in explaining environmental pollution in Ghana.

Methodology

Data

The study examines the impact of energy, agriculture, macroeconomic and human-induced indicators on environmental pollution using the SIMPLS regression model. A time series data spanning from 1971 to 2011 were employed from World Bank (2014) and FAO (2015) as shown in Table 1. Table 2 presents the descriptive statistical analysis of the study variables. Evidence from Table 2 shows that with the exception of EPH, all the remaining variables are positively skewed. In addition, EN2OMA, ECH4MM, EPH, FOSI, GDPP, IND, MNMA, MNMM, RES and STOCK exhibit a leptokurtic distribution while the remaining variables exhibit a platykurtic distribution. From the Jarque-Bera test statistic, EN2OMA, ECH4MM, EPH, FOSI, GDPP, IND, MNMA, MNMM, RES and STOCK do not fit the normal distribution, while the remaining variables are normally distributed based on 5% significance level. The figure shows the trend of the predictor variables versus the response variable. With the exception of EPH, it appears from Fig. 1 that all the variables have a positive monotonic relationship with CO_2.

Table 1 Data and variable definition

Abbreviation	Variable name	Unit	Source
CO_2	Carbon dioxide emissions	kt	World Bank (2014)
IND	Industry value added "as a proxy for industrialization"	Current LCU	World Bank (2014)
POP	Population	NA	World Bank (2014)
RES	Total reserves (includes gold)	Current US$	World Bank (2014)
TRD	Trade	% of GDP	World Bank (2014)
GDPP	GDP per capita	Current LCU	World Bank (2014)
FOSI	Fossil fuel energy consumption	% of total	World Bank (2014)
LIVE	Livestock production index (2004–2006 = 100)	%	World Bank (2014)
EPH	Electricity production from hydroelectric sources	%	World Bank (2014)
CROPI	Crop production index (2004–2006 = 100)	%	World Bank (2014)
BBCRDM	Biomass burned crop residues	t	FAO (2015)
ECH4En	Enteric emissions	Gg	FAO (2015)
ECH4MM	Methane emissions from manure management	Gg	FAO (2015)
EMCH4BCR	Methane emissions from burning crop residues	Gg	FAO (2015)
EMN2OBCR	Nitrous oxide emissions from burning crop residues	Gg	FAO (2015)
EMN2OCR	Nitrous oxide emissions from crop residues	Gg	FAO (2015)
EN2OMA	Nitrous oxide emissions from applied manure	Gg	FAO (2015)
MNMA	Nitrogen content of manure	kg	FAO (2015)
MNMM	Nitrogen content of manure management	kg	FAO (2015)
RCR	Crop residue	t	FAO (2015)
Stock	Stock of livestock	Head	FAO (2015)

Table 2 Descriptive statistical analysis

Variable/statistic	Mean	Median	Maximum	Minimum	Std. dev.	Skewness	Kurtosis	Jarque-Bera	Probability[a]
BBCRDM	654,173.9	665,195	1,135,500	276,160	220,611.4	0.2879	2.3291	1.3355	0.5129
CO_2	5035.238	4044.701	10,102.58	2295.542	2459.736	0.6855	2.1929	4.3238	0.1151
CROPI	59.96049	52.8900	131.9200	25.1	32.10517	0.7125	2.2322	4.4757	0.1067
ECH4EN	63.7949	61.2759	96.8172	44.3663	15.28686	0.5197	2.1346	3.1247	0.2096
ECH4MM	2.960583	2.7357	5.0481	2.0038	0.802109	1.0549	3.1498	7.6433	0.0219
EMCH4BCR	1.76628	1.7960	3.0659	0.7457	0.595659	0.2879	2.3290	1.3357	0.5128
EMN2OBCR	0.045812	0.0466	0.0795	0.0193	0.015454	0.2882	2.3270	1.3413	0.5114
EMN2OCR	0.345305	0.3310	0.6326	0.1631	0.126716	0.4378	2.1803	2.4576	0.2926
EN2OMA	0.207612	0.1995	0.3506	0.1393	0.048843	1.4745	4.5270	18.8392	0.0001
EPH	91.02664	98.9276	100.0000	53.41072	13.10556	−1.2724	3.3097	11.2275	0.0036
FOSI	23.17066	21.99753	40.79426	11.5289	6.562491	0.9526	3.4830	6.5994	0.0369
GDPP	275.9624	16.13755	2399.515	0.028321	563.6219	2.4090	7.9861	82.1265	0.0000
IND	1.33E+09	41,181,200	1.43E+10	45,700	2.87E+09	2.9282	11.9852	196.5128	0.0000
LIVE	79.1932	80.5400	127.5100	42.5700	22.3015	0.2495	2.5898	0.7129	0.7002
MNMA	9,271,656	8,908,200	15,652,400	6,224,200	2,180,329	1.4768	4.5301	18.9017	0.0001
MNMM	9,963,619	9,621,180	16,636,400	6,715,140	2,295,278	1.4411	4.4523	17.7943	0.0001
POP	15,586,682	15,042,736	24,928,503	8,827,273	4,847,325	0.3220	1.8888	2.8176	0.2444
RCR	17,938,625	17,193,600	32,859,500	8,472,450	6,582,574	0.4376	2.1798	2.4580	0.2926
RES	9.54E+08	4.37E+08	5.91E+09	43,092,215	1.30E+09	2.5046	8.9315	102.9695	0.0000
STOCK	24,337,141	18,109,700	63,682,000	11,484,700	13,821,325	1.3997	3.8776	14.7026	0.0006
TRD	54.05703	45.84812	116.0484	6.320343	29.8343	0.3255	2.0776	2.1777	0.3366

[a] The rejection of the null hypothesis of normal distribution

Partial least squares regression

The partial least squares regression involves the use of principal component analysis to decide on a regression model with the latent variables and the response variables. The SIMPLS regression model directly computes the partial least squares factors as a linear combination of the original study variables (De Jong 1993). The SIMPLS regression model was developed with the aim of explaining a specific optimality problem (i.e. maximizing covariance criterion between the predictor variables and the response variable, on condition that the predictor variable scores are orthogonal). As a result, it has been suggested that the SIMPLS regression model is, to some extent, superior over the non-linear iterative partial least squares (NIPALS) (Wise 2004).

Model estimation

Prior to the SIMPLS regression model, a linear regression analysis is estimated to examine the relationship between energy, agriculture, macroeconomic and human-induced indicators and environmental pollution, expressed as

$$\begin{aligned} CO_{2t} = {} & \beta_0 + \beta_1 \mathrm{IND}_t + \beta_2 \mathrm{POP}_t + \beta_3 \mathrm{RES}_t + \beta_4 \mathrm{TRD}_t + \beta_4 \mathrm{TRD}_t + \beta_5 \mathrm{GDPP}_t + \beta_6 \mathrm{FOSI}_t + \beta_7 \mathrm{LIVE}_t + \\ & \beta_8 \mathrm{EPH}_t + \beta_9 \mathrm{CROI}_t + \beta_{10} \mathrm{BBCRDM}_t + \beta_{11} \mathrm{ECH4En}_t + \beta_{12} \mathrm{ECH4MM}_t + \\ & \beta_{13} \mathrm{EMCH4BCR}_t + \beta_{14} \mathrm{EMN2OBCR}_t + \beta_{15} \mathrm{EMN20CR}_t + \beta_{16} \mathrm{EN20MA}_t + \beta_{17} \mathrm{MNMA}_t + \\ & \beta_{18} \mathrm{MNMM}_t + \beta_{19} \mathrm{RCR}_t + \beta_{19} \mathrm{RCR}_t + \beta_{20} \mathrm{Stock}_t + \varepsilon_t \end{aligned} \quad (1)$$

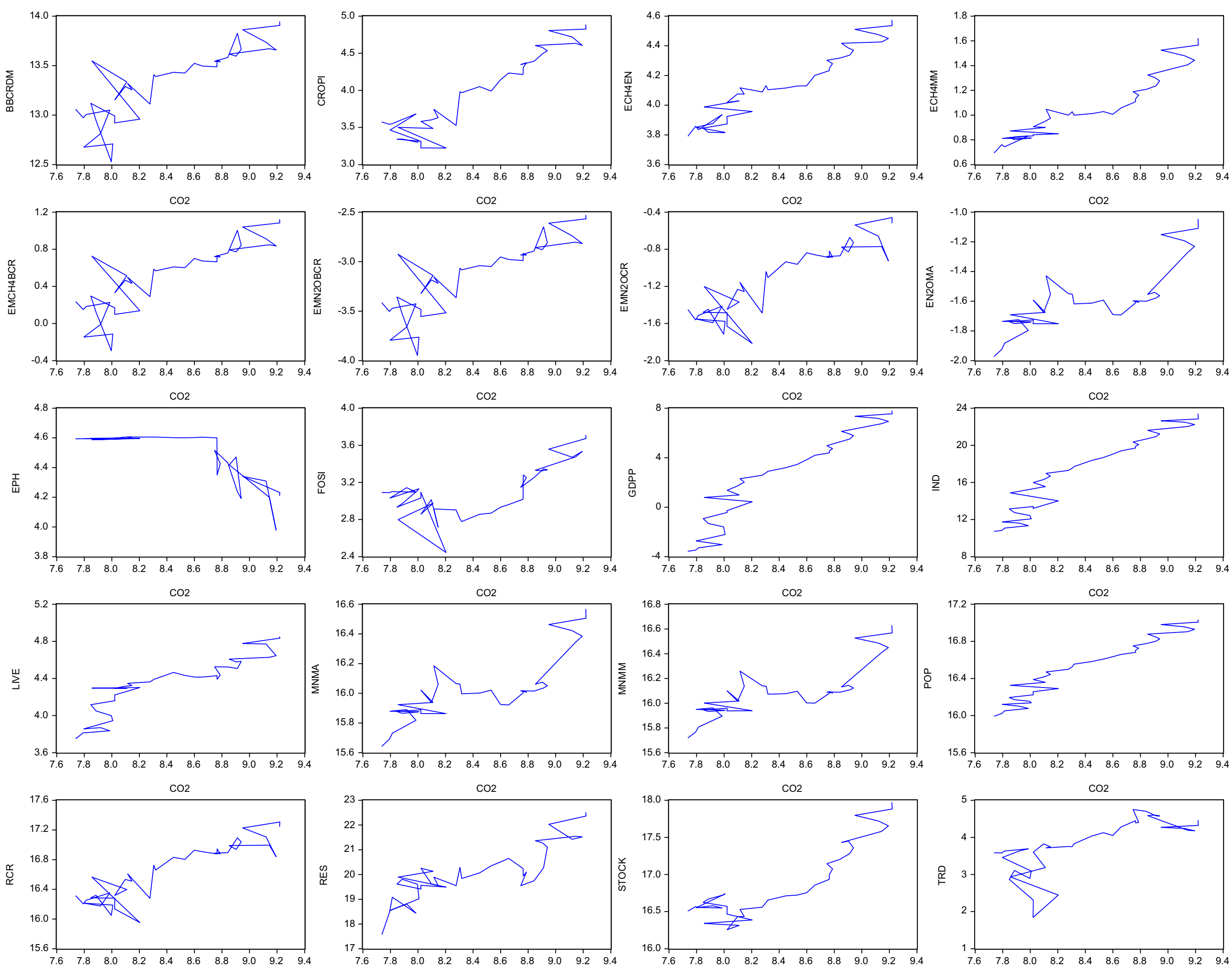

Fig. 1 Trend of predictor variables versus response variable

where β_0 represents the intercept, β_1, β_2, β_3,..., β_{20} represent the "projected change in the mean response of the predictor variables for each unit change in their value" and ε_t represents the white noise.

The partial least squares regression is grounded on the decomposition of the basic latent component:

$$Y = TQ^T + F \quad (2)$$

$$X = UP^T + E \quad (3)$$

where Y is an $n \times m$ matrix of the predictors, X is an $n \times p$-matrix of the responses, T and U are $n \times l$ matrices which represents the projections of Y and X (−scores), Q and P are $m \times l$ and $p \times l$ "orthogonal loading matrices", while F and E represent the error terms.

For brevity, the SIMPLS regression model is expressed as (Boulesteix and Strimmer 2007; De Jong 1993; Wise 2004)

$$t = X_0 w \quad (4)$$

where t is the score vector and w is its corresponding weight vector.

$$\text{Let}, X = X_0 \text{ and } Y = Y_0 \quad (5)$$

where $X = X_0$ is the centred and scaled matrix of the predictor variables and $Y = Y_0$ is the centred and scaled matrix of the response variable. X_0 and Y_0 are predicted by the partial least squares method via a regression on t

$$\hat{X}_0 = tp' \text{ where } p' = \left(t't\right)^{-1} t' X_0 \quad (6)$$

$$\hat{Y}_0 = tc', \text{where } c' = \left(t't\right)^{-1} t' Y_0 \quad (7)$$

where vectors p and c are the X-loading and Y-loading.

$t = X_0 w$ in Eq. 2 is the "specific linear combination" with a maximum covariance, $t = t'u$, and a response linear combination $u = Y_0 q$ which is characterized by the X-weight and Y-weight (w and q) that are proportional to the first left and right singular vectors of the covariance matrix $X_0 Y_0$. This cross-product matrix, $X_0 Y_0$ is deflated repeatedly for many latent variables/factors if is required.

Results and discussion

Multicollinearity examination

The variance inflation factor (VIF) shows how much the expected variance of the independent variable (ith) in the regression coefficient is increased above what it would be if the squared multiple correlations of the independent variable (R_i^2) amount to zero: a condition in which the ith independent variable is orthogonal to the other independent variables in the multivariate analysis.

$$\text{VIF}_i = \frac{1}{1 - R_i^2} \quad (8)$$

The variance inflation factor (VIF$_i$) is calculated for $\hat{\beta}_1$ from the above equation, where R_i^2 represents the coefficient of determination of the regression analysis. From here, multicollinearity can be calculated, thus VIF $\left(\hat{\beta}_1\right) > 10$.

VIF offers a realistic and intuitive warning of the effects of multicollinearity on the variance of the ith regression coefficient (O'brien 2007). The study employs the linear regression analysis to examine the multicollinearity among variables using the VIF. Table 3 shows evidence of a linear relationship between energy, agriculture, macroeconomic and human-induced indicators and carbon dioxide emissions. However, according to the rule of thumb, a VIF > 10 indicates an "excessive multicollinearity" among the independent variables (Graham 2003; Griffith and Harvey 2001; Mansfield and Helms 1982; O'brien 2007); thus, the SIMPLS regression analysis in this study is worthwhile.

Assessment of SIMPLS regression

The leave-one-out cross-validation refits the model repeatedly leaving out a single observation and then used to derive a prediction for the left-out observation. It is believed that the leave-one-out cross-validation gives an "almost unbiased

Table 3 Linear regression analysis

Source	DF	Adj SS	Adj MS	F value	P value
Regression	20	2.39E+08	11,952,080	80.47	0.0000
Term	Coef	SE coef	T value	P value	VIF
Constant	5035.2	60.2	83.66	0.0000	
IND	580	645	0.9	0.3800	112.16
POP	3331	1127	2.95	0.0080	342.33
RES	−403	355	−1.14	0.2700	33.86
TRD	−117	285	−0.41	0.6850	21.91
GDPP	−901	1206	−0.75	0.4640	391.41
FOSI	−201	307	−0.65	0.5210	25.42
LIVE	−191	731	−0.26	0.7960	144
EPH	−699	223	−3.14	0.0050	13.39
CROPI	−2188	1088	−2.01	0.0580	318.81
EMCH4BCR	445,299	1,099,936	0.4	0.6900	3.26E+08
EMN2OBCR	−22,938	24,729	−0.93	0.3650	164,696.5
BBCRDM	−423,457	1,100,536	−0.38	0.7040	3.26E+08
EMN2OCR	−104,931	183,343	−0.57	0.5730	9,052,993
RCR	106,232	183,191	0.58	0.5680	9,037,986
Stock	1274	3958	0.32	0.7510	4219.98
ECH4En	−33,760	23,169	−1.46	0.1610	144,574.6
EN2OMA	−26,835	57,210	−0.47	0.6440	881,463.7
MNMA	−308,234	179,926	−1.71	0.1020	8,718,736
ECH4MM	44,522	33,239	1.34	0.1950	297,546
MNMM	323,125	169,114	1.91	0.0700	7,702,406

Table 4 Cross validation with SIMPLS

Number of factors	Root Mean PRESS	Plot	Van Der Voet T²	Prob > Van Der Voet T²
0	1.0250		17.6956	<.0001*
1	0.3294		4.6689	0.0240*
2	0.2730		1.0416	0.3350
3	0.2465		0.1136	0.7580
4	0.2409		0.0002	0.9920
5	0.2407		0.0000	1.0000
6	0.2525		1.3843	0.2740
7	0.2534		1.0111	0.3160
8	0.2832		2.2295	0.0740
9	0.2990		1.9378	0.1670
10	0.3053		1.5126	0.3370
11	0.3401		1.5555	0.3390
12	0.5083		1.1624	0.3520
13	0.7452		1.0491	0.3780
14	1.0170		0.9983	0.5350
15	0.5333		0.9450	0.6160

Note: The minimum root mean PRESS is 0.2407 and the minimizing number of factors is 5

estimator of the generalization properties of the statistical models" (Cawley and Talbot 2004). A leave-one-out cross-validation and a randomization test known as Van der Voet T^2 are used in the SIMPLS method to ascertain whether a

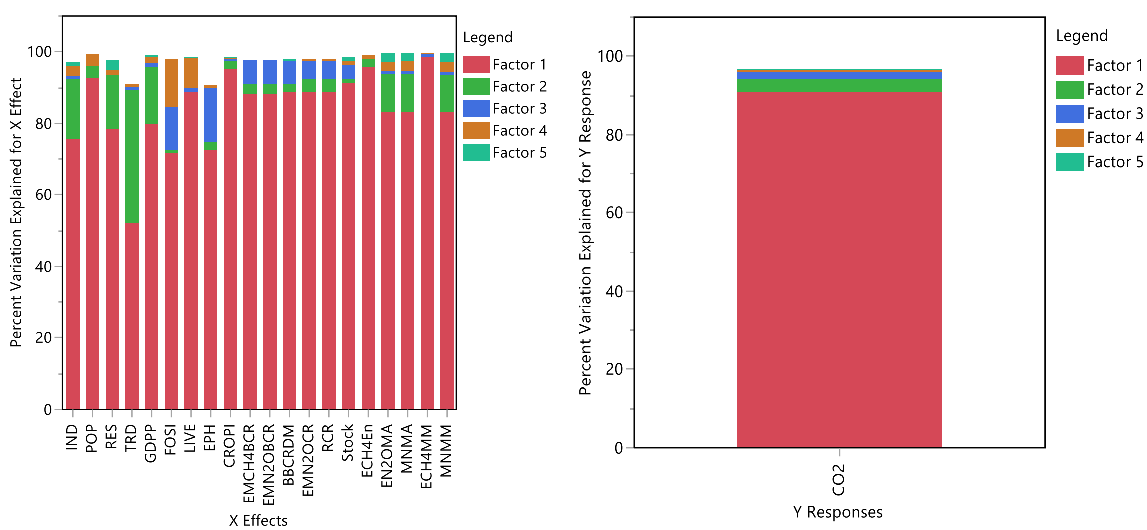

Fig. 2 **a** Percent variation explained for *X* effects and **b** percent variation explained for *Y* responses

Table 5 Variable importance analysis

Variable	VIP
IND	0.8905
POP	1.1438
RES	0.9083
TRD	0.9417
GDPP	0.9148
FOSI	0.9228
LIVE	1.0224
EPH	1.0765
CROPI	1.0728
EMCH4BCR	1.0008
EMN2OBCR	1.0028
BBCRDM	1.0012
EMN2OCR	1.0089
RCR	1.0099
Stock	1.0299
ECH4En	1.0842
EN2OMA	0.9331
MNMA	0.9356
ECH4MM	1.0927
MNMM	0.9591

model with a specific number of latent variables is different from the selected optimal model by the root mean predicted residual error sum of squares (PRESS). The Van der Voet T^2 test is based on the null hypothesis that the squared residuals for both models have the same distribution. The PRESS is calculated as $\mathrm{PRESS} = \sum_{i=1}^{n} \left(y_i - y_{(i)i}\right)^2$, where y is the experimental response, y is the fitted value, and $(i)i$ indicates that the response is predicted by the model estimated when the ith observation was left out from the training set. Evidence from Table 4 shows that the minimum root mean PRESS is 0.2407, and the minimizing number of factors in the SIMPLS method is 5. After the selection of the number of optimal latent variables, the study examines the percentage variation explained in SIMPLS model. Evidence from Fig. 2 shows that almost 98% of variation is explained by the predictor variables, while 97% of variation is explained by the response variable.

The variable importance analysis

The importance of the predictor variables in explaining carbon dioxide emissions is estimated using the variable importance of projection (VIP), which examines the contribution of each predictor variable based on the variance explained by each SIMPLS latent variable (Mehmood et al. 2012; Wold et al. 2001). The first analysis in the SIMPLS model led to the deletion of some variables that had VIP value lesser than 0.83, since literature considers them as irrelevant (Gosselin et al. 2010). Eriksson et al. (2001) categorizes the explanatory variables based on their VIP, thus "highly influential" (VIP > 1), "moderately influential" (0.8 < VIP < 1) and "less influential" (VIP less than 0.8). In the examination of the variable importance analysis in Table 5, the explanatory variables can be categorized based on their VIP value. IND, RES, TRD, GDPP, FOSI, EN2OMA, MNMA and MNMM can be

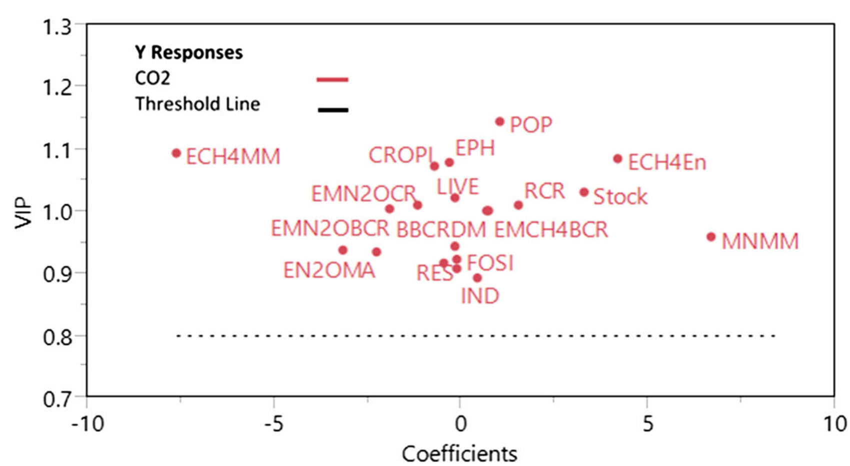

Fig. 3 VIP versus coefficients for centred and scaled data

Table 6 Model coefficients for centred and scaled data

Coefficient	CO2
Intercept	0.0000
IND	0.4366
POP	1.0303
RES	-0.1047
TRD	-0.1301
GDPP	-0.4626
FOSI	-0.1176
LIVE	-0.1439
EPH	-0.2976
CROPI	-0.7094
EMCH4BCR	0.7443
EMN2OBCR	-1.9058
BBCRDM	0.6877
EMN2OCR	-1.1297
RCR	1.5621
Stock	3.2883
ECH4En	4.2232
EN2OMA	-2.2673
MNMA	-3.1275
ECH4MM	-7.6173
MNMM	6.6878

classified as moderately influential variables while POP, LIVE, EPH, CROPI, EMCH4BCR, EMN2OBCR, BBCRDM, EMN2OCR, RCR, Stock, ECH4En and ECH4MM can be classified as highly influential variables. Figure 3 presents a plot of VIP versus coefficients for centred and scaled data. The black dotted lines represent the "threshold line", while the red-solid-circles represent the level of carbon dioxide emissions. Values of the coefficient below zero represent a negative contribution towards carbon dioxide emissions, while values greater than zero represent a positive contribution towards carbon dioxide emissions. It appears from Fig. 3 that the higher the VIP, the higher the coefficient contribution and the lower the VIP, the lower the coefficient contribution.

Impact analysis

The impact analysis of energy, agriculture, macroeconomic and human-induced indicators on environmental pollution is evident in Table 6. Evidence from Table 6 shows that a 1% increase in methane emissions from manure management will reduce carbon dioxide emissions by 7.62%. According to EPA (2016), the emissions from methane can be reduced and captured if manure management strategies are altered through animal feeding practices or at the livestock operations. The nitrogen content of manure increased by 1% will reduce carbon dioxide emissions by 3.13%. An increase in nitrous oxide emissions from applied manure by 1% will reduce carbon dioxide emissions by 2.27%. Nitrous oxide emissions from burning crop residues increased by 1% will reduce carbon dioxide emissions by 1.91%. Nitrous oxide emissions from crop residues increased by 1% will reduce carbon dioxide emissions by 1.13%. Crop production index increased by 1% will reduce carbon dioxide emissions by 0.71%. GDP per capita increased by 1% will reduce carbon dioxide emissions by 0.46%, which means that an increase in a Ghana's economic growth may lead to a reduction in environmental

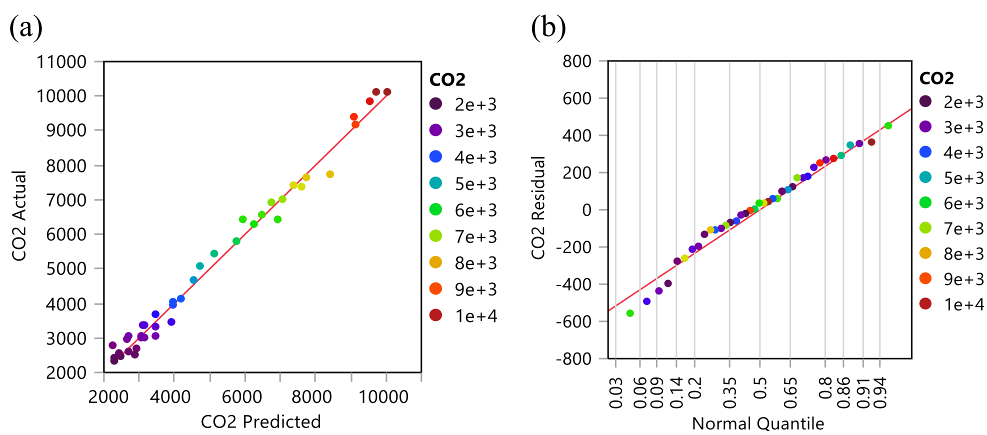

Fig. 4 Diagnostics plots. **a** Actual by predicted plot. **b** Residual normal quantile plot

pollution. Electricity production from hydroelectric sources increased by 1% will reduce carbon dioxide emissions by 0.30%, thus increasing renewable energy sources in Ghana's energy portfolio will help mitigate carbon dioxide emissions. Livestock production index increased by 1% will reduce carbon dioxide emissions by 0.14%. Increasing trade by 1% will reduce carbon dioxide emissions by 0.13%. Fossil fuel energy consumption increased by 1% will reduce carbon dioxide emissions by 0.12%. Increasing the total reserves including gold by 1% will reduce carbon dioxide emissions by 0.10%, thus halting the illegal mining and chainsaw operations will help reduce carbon dioxide emissions.

In contrast, a 1% increase in industrialization will increase carbon dioxide emissions by 0.44%. A 1% increase in biomass burned crop residues will increase carbon dioxide emissions by 0.69%. Methane emissions from burning crop residues increased by 1% will increase carbon dioxide emissions by 0.74%. Population increased 1% will increase carbon dioxide emissions by 1.03%. A 1% increase in crop residue will increase carbon dioxide emissions by 1.56%. A stock of animals increased 1% will increase carbon dioxide emissions by 3.29%. Increasing enteric emissions by 1% will increase carbon dioxide emissions by 4.22% and a 1% increase in the nitrogen content of manure management will increase carbon dioxide emissions by 6.69%. However, the value of the intercept indicates that when there is no increase in the energy, agriculture, macroeconomic and human-induced indicators, there will be no carbon dioxide emissions.

Diagnostics of the SIMPLS method

The SIMPLS regression method was subjected to diagnostic checks to estimate the independence of the residuals in the model (Fig. 4). Evidence from the diagnostic plots shows that the actual response and the predicted variable nearly fit on the regression line along with evidence of normal distribution by the residual normal quantile plot.

SIMPLS forecasting and performance

Figure 5 shows the actual versus SIMPLS predicted CO_2. The study explores the usefulness of the SIMPLS regression method in predicting the response variable. Evidence from Fig. 5 shows that the SIMPLS predicted carbon dioxide emissions nearly fits the original data with a mean absolute percentage error (MAPE) of 5.16% which is acceptable. By the addition of a trend line, the following equation is generated based on sixth polynomial: $y = 3E{-}05x^6 - 0.003x^5 + 0.1045x^4 - 1.0881x^3 - 2.7697x^2 + 127.4x + 2200.3$ with an $R^2 = 0.9742$. Thus, 97% of the SIMPLS predicted carbon dioxide emissions were explained by the sixth polynomial equation.

Conclusion and policy recommendation

The study examines the impact of energy, agriculture, macroeconomic and human-induced indicators on environmental pollution from 1971 to 2011 using the SIMPLS regression model. There was evidence of a linear relationship between energy, agriculture, macroeconomic and human-induced indicators and carbon dioxide emissions.

The SIMPLS regression model shows that an increase in Ghana's crop production index by 1% will reduce carbon dioxide emissions by 0.71%. Crop production accounts for 66.2% of the agricultural GDP in Ghana; however, indigenous farming methods and practices that appear to be unsustainable still play a critical role in the farming communities (Asumadu-Sarkodie and Owusu 2016h). Therefore, the introduction of

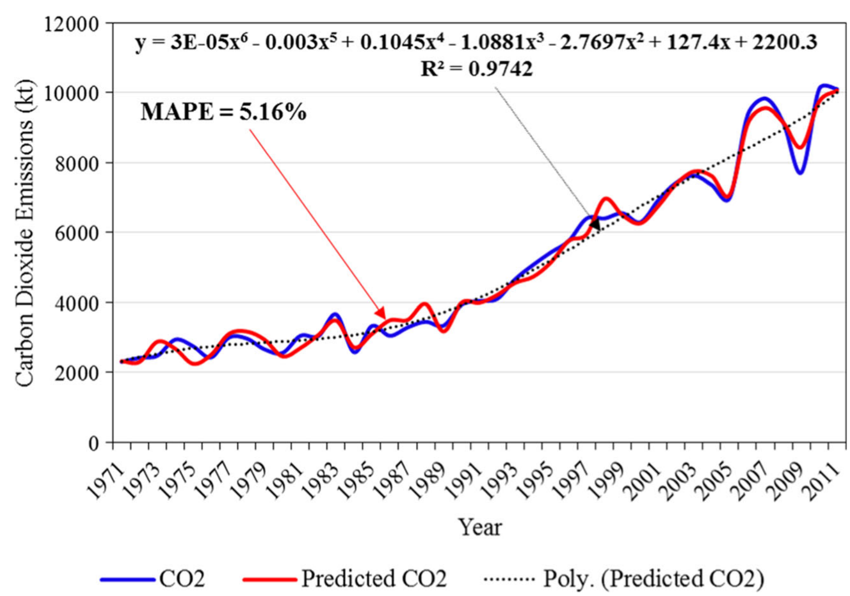

Fig. 5 Actual versus SIMPLS predicted CO_2

modern and sustainable agricultural practices in the local communities through awareness creation would help in the fight against climate change.

Increasing GDP per capita and electricity production from hydroelectric sources by 1% will reduce carbon dioxide emissions by 0.46 and 0.30%, respectively. Ghana became a middle income country in 2011 through a development agenda enshrined in the Growth and Poverty Reduction Strategy (GPRS) by increasing energy supply and labour force and expanding the social infrastructures to meet the needs of the population. Nonetheless, Ghana has suffered a decline in the economy due to inadequate energy supply, load shedding and power fluctuations that has crippled both public and private businesses, as well as industries. The energy crisis resulted from the overdependence on the hydropower for power generation, which became unreliable due to rainfall variations. The recent condition has resulted in a reduction in the labour force affecting the productivity of the country. A reduction in purchasing power and the inability of some Ghanaians to afford clean alternative sources of energy has led to the abuse of woodfuel especially firewood and charcoal for cooking and heating purposes which propels environmental pollution. Incorporating other renewable and clean energy technologies to the energy portfolio will help safeguard the economy by creating decent jobs and increase the GDP per capita which will directly increase the willingness to pay for clean energy technologies, thereby reducing environmental pollution in the long run.

In contrast, a 1% increase in industrialization, biomass burned crop residues, methane emissions from burning crop residues, crop residue, population, stock of animals, enteric emissions and nitrogen content of manure management will increase carbon dioxide emissions by 0.44, 0.69, 0.74, 1.03, 1.56, 3.29, 4.22, and 6.69%. Even though, livestock production accounts for only 6.1% of Ghana's agricultural GDP but contributes immensely towards environmental pollution, as a result of enteric emissions and nitrogen content of manure management. The negative effects of enteric emissions and nitrogen content of manure management can be transformed into a positive use by introducing carbonization technologies for energy generation. Also, biomass burned crop residues and crop residues can be utilized into useful energy through biomass-energy conversion technologies. Cycling usage will help reduce/eradicate methane emissions from burning crop residues, thereby mitigating climate change and its impacts.

The following policy recommendations are proposed in the study:

Integrating climate change measures into national energy policies, sustainable agricultural policies, strategies and planning will increase institutional capacities towards adopting climate change measures, adaptation, early warnings and impact reduction.

Promoting sustainable industrial services through the inclusion of climate change policies into their core values would help in climate change awareness and adaptation options.

Industrial policies that aim at promoting local technological development, scientific research, innovation and creativity, access to affordable internet and the provision of conducive environmental policies will propel Ghana's effort towards achieving sustainable industrialization.

Finally, there is the need for an enhanced local financial institutional capacity to boost access to financial services, insurance and banking in order to attract foreign investments, create jobs and propel the country's financial development.

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