Heliyon 10 (2024) e25416

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Measuring the impact of responsible factors on CO_2 emission using generalized additive model (GAM)

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A R T I C L E I N F O

Keywords:
CO_2 emissions
Nonparametric model
Generalized additive model
Bangladesh

A B S T R A C T

The indicators of economic and sustainable development ultimately significantly depend on carbon dioxide (CO_2) emissions in every country. In Bangladesh, there is an increasing trend in population, industrialization, as well as electricity demand generated from different sources, ultimately increasing CO_2 emissions. This study explores the relationship between CO_2 emissions and other significant relevant indicators. Moreover, the authors aimed to identify which model is effective at predicting CO_2 emissions and assess the accuracy of the prediction of different models. The secondary data from 1971 to 2020, was collected from the World Bank and the Bangladesh Road Transport Authority's publicly accessible website. The generalized additive model (GAM), the polynomial regression (PR), and multiple linear regression (MLR) were used for modeling CO_2 emissions. The model performance is evaluated using the Bayesian information criterion (BIC), Akaike information criterion (AIC), Root mean square error (RMSE), R-square, and mean square error (MSE). Results revealed that there are few multicollinearity problems in the datasets and exhibit a nonlinear relationship among CO_2 emissions. Among the models considered in this study, the GAM model has the lowest value of RMSE = 0.008, MSE = 0.000063, AIC = −303.21, BIC = −266.64 and the highest value of R-squared = 0.996 compared to the MLR and PR models, suggesting the most appropriate model in predicting CO_2 emissions in Bangladesh. Findings revealed that the total CO_2 emissions and other relevant risk factors is non-linear. The study suggests that the Generalized additive model regression technique can be used as an effective tool for predicting CO_2 emissions in Bangladesh. The authors believed that the findings would be helpful to policymakers in designing effective strategies in the areas of a low-carbon economy, encouraging the use of renewable energy sources, and focusing on technological advancement that reduces CO_2 emissions and ensures a sustainable environment in Bangladesh.

1. Introduction

Greenhouse gas (GHG) emissions are on the rise globally, which has caused the earth to continue getting hotter and to experience a variety of environmental problems everywhere. It is agreed that if aggressive steps are not taken to reduce the rising worldwide trend in GHG emissions, the earth's surface temperature will likely rise by about 4 °C by 2050 [1]. As a result, it could lead to extreme weather conditions and unprecedented sea level rises [2]. Although GHGs include a number of gases that harm the environment,

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https://doi.org/10.1016/j.heliyon.2024.e25416
Received 24 October 2023; Received in revised form 13 January 2024; Accepted 25 January 2024
Available online 6 February 2024
2405-8440/

Carbon Dioxide (CO_2) is the most significant GHG and is often referred to as the main cause of global warming [3]. As a result, in order to limit the degradation of the environment, environmental experts frequently urge the implementation of carbon-abating laws that can restrict the discharge rate of CO_2 into the atmosphere [4]. The quantity of CO_2 that is typically taken from the atmosphere by plant photosynthesis and the seas almost equals that which is emitted by living creatures, humans, and from wetlands, volcanoes, and other sources [5]. However, human activities are upsetting this equilibrium because they produce more CO_2 from the combustion of fossil fuels including coal, gas, and petroleum products as well as from electricity production, transportation, industry, and household use [6].

These imbalances are thought to have greenhouse effects such as agricultural and natural ecosystem damage, global warming, melting polar ice sheets and caps, increasing sea levels and subsequent coastal flooding, and more. Global greenhouse gas (GHG) emissions are on the rise as a result of human activity, which means that atmospheric concentrations of CO_2, methane (CH_4), nitrous oxide (N_2O), perfluorocarbons (PFCs), hydrofluorocarbons (HFCs), and sulfur hexafluoride (SF_6) have significantly increased [7]. According to the Intergovernmental Panel on Climate Change (IPCC) [8] shows that CO_2 is the most prevalent greenhouse gas (GHG), accounting for 79.4 % of all worldwide GHG emissions, with contributions from N_2O, CH_4, and other gases of 11.5 %, 6.2 %, and 3 %, respectively. In recent years, one of the most significant challenges has been the impact of global warming on climate change. Researchers noted that with a doubling the concentration of CO_2, the average global temperature will likewise increase by 3 °C - 4 °C [9]. In 2021, the IPCC released revised estimates of the likelihood of exceeding the 1.5 °C global warming level in the coming decades, concluding that unless there are immediate, quick, and large-scale reductions in greenhouse gas emissions, limiting warming to 1.5 °C or even 2 °C will be out of reach [8]. Furthermore, the United Nations emphasized the urgent need for clean and reliable energy, sustainable economic growth, and technological advancements in different sustainable development goals (SDGs 7, 8, 9, and 13) [10]. However, Bangladesh is developing rapidly and one of the most climate change-vulnerable countries in the globe [11]. Bangladesh is placed seventh among the countries most vulnerable to climate change, according to the Global Climate Risk Index 2021, which poses a further risk to the country's ability to sustain its economy. Climate change vulnerabilities lost Bangladesh about USD 3.72 billion between 2000 and 2019, and if the government does not implement appropriate sustainable solutions, the cost will be increased in the future [12].

Following trade and financial liberalization in the 1990s, many industrial plants were developed throughout Bangladesh in diverse regions (Dhaka, Chittagong, Narayanganj, Gazipur, etc.); however, environmental concerns were not taken seriously at the time. Therefore, industrial firms' unsustainable activities (such as the processing of raw leather, chemical waste, and deforestation brought on by urbanization) are to blame for the ongoing degradation of the natural environment [13]. Climate change has recently posed a challenge to economic development plans in many developing or recently industrialized nations, especially for those with weak industrialization. According to a prior study, Bangladesh's industrial pollution is having a significant negative impact on a lot of individuals [14]. Another study that describes the national pollution profile also demonstrates that a significant portion of the pollution burden in the nation is contributed by industrial sub-sectors [15]. According to Bala and Yusuf [16], Bangladesh's current industrial concerns, which are accountable for environmental pollution and public health risks, must implement the necessary precautions to prevent pollution. The threat of global warming as well as climate change has been growing in Bangladesh over the past 20 years due to fast industrialization, an increase in population, and significant changes in the development of trade and the financial sector [14]. For Bangladesh, the issue of climate change is crucial. According to the hypostheis of environmental Kuznets curve (EKC), many economies anticipate that their carbon emissions will increase, causing the planet to warm even more [17]. The presence of the EKC is a contentious matter, and it is possible that different countries will have different output-emission nexuses based on their level of industrialization, trade patterns with major trading partners, and energy consumption. These key elements are linked to emissions, which are in turn strongly connected to Bangladesh's relationships with regard to energy consumption. In addition, a number of additional variables, such as the composition of growth, the kind of economic activities, the degree of industrialization in foreign commerce, and financial development, have an impact on Bangladesh's emissions-energy-output nexus [18].

Several researchers used different techniques to predict their target variables. Nowadays, several nonlinear models, machine learning, and/or artificial algorithms are widely used in several fields for prediction purposes though the interpretation of parameters is quite challenging [19–30]. However, the potential influence of responsible variables for reducing emission in Bangladesh has become an interesting issue among cutting-edge researchers, there are few studies utilizing non-parametric approaches to investigate the potential. This study employs the GAM approach (non-parametric) for assessing the dynamic implications of transportation, industrialization, non-renewable energy consumption, economic growth, population growth rate, chemical fertilizer use, and agricultural land area on CO_2 emissions in Bangladesh in an attempt to fulfill this research gap. In different ways, this study contributes to current research and policies in Bangladesh, making it valuable. First, novel findings from a comprehensive non-parametric analysis of the association between CO_2 emissions and contributing factors are provided, this study addresses the gap in the amount of existing academic research. Second, this research is novel given that it determines the possible impacts of transportation, industrialization, chemical fertilizer use, non-renewable energy use, and agricultural land area on CO_2 emissions in Bangladesh which is a groundbreaking attempt to determine the relationship between CO_2 emissions and the previous variables in the context of Bangladesh. Third, the most recent and comprehensive data available from 50 years (1971–2020) was used in this investigation. Forth, the GAM, the polynomial regression (PR), and multiple linear regression (MLR) were used for modeling CO_2 emissions. The accuracy of the results was evaluated using the BIC, AIC, RMSE, R-square, and MSE. Finally, the study's findings will be helpful to policymakers for developing effective strategies in the areas of low-carbon economy, sustainable transportation, green industrialization, promoting renewable energy use, sustainable fertilizer use, and sustainable agriculture area management, all of which would ensure sustainable environment in Bangladesh by lowering CO_2 emissions. The investigation's findings are also useful for evaluating environmental strategies and developing novel strategies that will more effectively prepare Bangladesh for a world temperature of 1.6 °C by strengthening plans for action and policy which will reduce the impacts of climate change and ensure long-term sustainable development and environmental quality. The findings of this study might benefit developing countries that aim to strengthen their mitigation and adaptation plans for climate change while also building effective strategies to achieve environmental sustainability.

2. Methods

2.1. Data and variables

In this study, annual time series data over the period 1971 to 2020 for the ten variables are used. These variables included CO_2 emissions (CEs) (metric tons per capita) as the response and GDP (annual growth), population growth (PGR) (annual%), industry value added (IVG) (% of GDP), manufacturing value added (MVG) (% of GDP), and the total number of registered motor vehicles (TNRMV) (lakhs), as well as electricity production from oil sources (EPOS) (% of total), and electricity production from gas sources (EPGS) (% of total), Agriculture land (AGLA) (% of land area), and Fertilizer consumption (FC) (unit of fertilizer production) as covariates. The World Development Indicators database of the World Bank [31] provided the secondary data, which is accessed through the following link: https://data.worldbank.org/country/BD. Additionally, information about the total number of registered motor vehicles may be found at the Bangladesh Road Transport Authority website http://www.brta.gov.bd.

2.2. Study design

The first step in identifying the research gap is to thoroughly evaluate the literature on the study of CO_2 emissions. The research's study design is shown in Fig. 1, as can be seen. Phase one also confirms the factors' identification and the way in which they relate to the overall CO_2 emissions. The right model is chosen during phase two. The diagnostic evaluation and prediction-making are tasks for the last phase.

2.3. Multiple linear regression (MLR)

[32]Using the usual notation, the equation of multiple linear regression is presented in equation (1):

$$\begin{aligned} CO_2\ emission = {} & \beta_0 + \beta_1 GDP + \beta_2 PGR + \beta_3 IVG + \beta_4 MVG + \beta_5 TNRMV + \beta_6 EPOS \\ & + \beta_7 EPGS + \beta_8 AGLA + \beta_9 FC + \varepsilon \end{aligned} \tag{1}$$

Where $\beta_i;\ i = 1, 2, \ldots, 9$ are the coefficients of the covariates used in this study and ε is the random error.

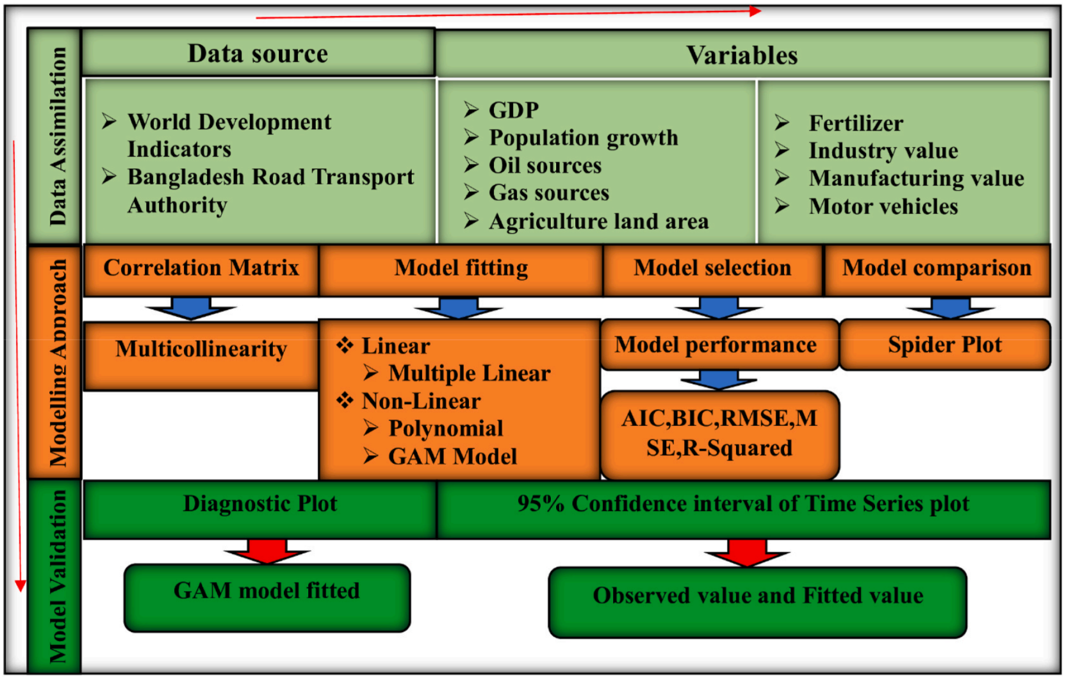

Fig. 1. Study design.

2.4. Multicollinearity checking

Multicollinearity arises in a multivariate regression model when more than two explanatory variables are highly correlated linearly. Several researchers have proposed the variance inflation factor (VIF) for multicollinearity [33] and presented in equation (2).

$$VIF = \frac{1}{1 - R^2} = \frac{1}{tolerance}. \tag{2}$$

The $VIF = 1$ indicates the absence of multicollinearity. The value $1 < VIF < 5$, suggests moderate multicollinearity and the value of VIF more than or equal to 5 indicates the higher multicollinearity [34].

2.5. Non -linear regression

Nonlinear regression is the representation of observational data by a function that depends on one or more independent variables. The data are fitted using a strategy of iterative approximations [35]. A simple nonlinear regression model is stated in equation (3):

$$Y = f(X, \beta) + \varepsilon \tag{3}$$

where X is a matrix of predictors, β is a parameters vector, f (.) is a known function, and ε is the error term.

2.6. Polynomial regression

In polynomial regression, the relationship between the independent variable X and the dependent variable Y is represented as an n th degree polynomial in X. A linear relationship might not hold true in many circumstances [36]. The general form of p th degree polynomial model can be given in equation (4),

$$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \ldots + \beta_p x^p + \varepsilon. \tag{4}$$

2.7. Piece-wise polynomial spline

The set of all piecewise polynomial functions of order k with break sequence ξ is presented in equation (5) [37],

$$\prod < k, \xi. \tag{5}$$

We can obtain the fitted values by simply assigning independent cubic polynomials to four intervals of X with cutoffs at $\{C_1, C_2, C_3\}$ as shown in equation (6).

$$\widehat{Y} = \begin{cases} \beta_{10} + \beta_{11}X + \beta_{12}X^2 + \beta_{13}X^3 \; for \; X < c_1 \\ \beta_{20} + \beta_{21}X + \beta_{22}X^2 + \beta_{23}X^3 \; for \; c_1 \leq X < c_2 \\ \beta_{30} + \beta_{31}X + \beta_{32}X^2 + \beta_{33}X^3 \; for \; c_2 \leq X \leq c_3 \\ \beta_{40} + \beta_{41}X + \beta_{42}X^2 + \beta_{43}X^3 \; for \; c_3 \leq X. \end{cases} \tag{6}$$

2.8. Generalized additive model (GAM)

In GAM model, the linear response variable linearly depends on some predictor variables' unknown smooth functions, with the main focus being on inference regarding these smooth functions [38]. Trevor Hastie and Robert Tibshirani created GAMs in the beginning to combine additive modeling with generalized linear modeling properties [39]. The naive Bayes generative model's discriminative generalization can be seen in them. A GAM takes the following form in the regression setting given in equation (7):

$$g\left(E\left[Y \middle| X_1, X_2, \ldots, X_p\right]\right) = \mu + f_1(X_1) + f_2(X_2) + \ldots + f_p\left(X_p\right) \tag{7}$$

here, Y is the continuous response, X_1, X_2, …, X_p are the covariates, and $f_1(.) + \ldots + f_p(.)$ are the unspecified smooth (nonparametric) functions. In order to link the expected value of Y to the predictor variables via a link function g provided in equation (8),

$$g(E(Y)) = \beta_0 + f_1(x_1) + f_2(x_2) + \ldots \tag{8}$$

The function f_i may be described non-parametrically, or semi-parametrically, merely as "smooth functions", to be estimated using nonparametric means, or they may be functions with a specified parametric form e.g., a polynomial or an unpenalized regression spline of a variable. Therefore, a typical GAM might utilize a factor model for f_1 (x_1) and a smoothing function, such as a locally weighted mean, for f_2 (x_2).

2.9. Model selection criteria

2.9.1. Akaike information criterion (AIC)

The AIC is a statistical model quality metric that assesses the goodness of fit. A lower of AIC value suggest a better model [40]. It is defined as

$$AIC = n \times \log\left(\frac{S_e}{n}\right) + 2p$$

where n is the total number of observations, p is the number of parameters, and S_e is the sum of squared errors.

2.9.2. Bayesian information criterion (BIC)

Comparable to AIC, BIC penalizes models with additional parameters more severely [40]. It can be written as

$$BIC = n \times \log\left(\frac{S_e}{n}\right) + p \times \log(n)$$

2.9.3. Root mean squared error (RMSE)

This represents the square-root of average difference between the predicted values and the actual values. It is commonly used in regression analysis, where the goal is to minimize the error [41]. It can be defined as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f(x_i) - y_i)^2}$$

where n is the total number of observations, x_i and y_i are the predictor and response variables for the i^{th} observation ,$f(x_i)$ is the estimated value at x_i .

2.9.4. Mean squared error (MSE)

This is similar to the RMSE but is a squared error term [41]. It is useful for comparing the accuracy of several models and can be written as

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(f(x_i) - y_i)^2.$$

3. Results

To explore the characteristics of the variables, using exploratory data analysis as well as time series plots, we investigated the data. Table 1 illustrates the descriptive statistics of the chosen variables in this study.

The amount of CO_2 emissions in Bangladesh varies just slightly, with an average value of 0.20 and a standard deviation (SD) of 0.15. The range of CO_2 emissions is 0.53, which implies that there are some really high CO_2 emissions in the country. The minimal CO_2 emission value is 0.04, which could be an outlier or a reporting mistake. The maximum CO_2 value is 0.58, indicating that the country has significant CO_2 emissions. GDP (annual growth) has a mean value of 4.34 and a SD of 3.68. The numbers are −13.97 and 9.59, respectively, for the minimum and maximum. The variable population growth (% annual), with an average value of 1.82 and a SD of 0.55. With values ranging from 0.88 to 2.77, the population growth range is wide. IVG is a variable that represents the industry value added (% of GDP) for the country. With a SD of 5.70, the industry value ranges from 6.06 to 32.91, with an average value of 21.71. EPGS represents the electricity production from gas sources of the country, with an average value of 71.02 and a SD of 17.74. With a range from 34.69 to 91.10, the EPGS value has a wider range than other variables. EPOS is a variable that represents the electricity production from oil sources for the country. The SD is 11.48 and the average value is 17.05. From 1.77 to 43.11, the EPOS value range. The total number of motor vehicles in the country that are represented by the variable TNRMV. The TNRMV's average value ranges from 0.89 to 45.69, with a SD of 11.05 and a range of values of 0.89 to 0.89. The AGLA is represented by the agriculture land area of the country. It has a SD of 2.90, an average value of 74.33, and the AGLA values vary from 70.09 to 80.23. The range of FC values, from 0.90 to 5.73, and the average value of fertilizer consumption is 2.43 with a SD of 1.72. MVG is a variable that represents the manufacturing (including construction) value added for the country. MVG has an average value of 14.26 and a SD 3.56. MVG values vary from 3.98 to 21.21 [Table 1].

Table 1
Descriptive statistics of the selected variables.

Name of the variable	Mean	Standard Deviation	Range	Min	Max
CEs	0.20	0.15	0.54	0.04	0.58
GDP	4.34	3.68	23.57	−13.97	9.59
PGR	1.82	0.55	1.89	0.88	2.77
IVG	21.71	5.70	26.85	6.06	32.91
EPGS	71.02	17.74	56.41	34.69	91.10
EPOS	17.05	11.48	41.34	1.77	43.11
TNRMV	9.14	11.05	44.80	0.89	45.69
FC	2.43	1.72	8.01	0.90	5.73
AGLA	74.33	2.90	10.14	70.09	80.23
MVG	14.26	3.56	17.22	3.98	21.21

Fig. 2 shows that CO_2 emissions have a positive correlation with most of the factors, meaning that when the values of these variables increase, the CO_2 tends to increase as well. Studies have found a strong positive association between CEs (CO_2 emission) and TNRMV (Motor vehicles), with a correlation value of 0.96. This suggests that as a country's motor vehicles increase, it tends to attract more CO_2 emissions. The industrial value added (IVG), which has a correlation value of 0.84 with CEs, also has a strong positive relationship with them. Increasing industry value added will result in increased CO_2 emissions. Additionally, it is found that Manufacturing Value Added (MVG) and CEs are strongly positively correlated, with a correlation value of 0.78, indicating that nations with greater MVG tend to attract more CO_2 emissions. There is also a positive correlation between fertilizer consumption (FC) and CEs, with a correlation value of 0.76, indicating that countries with higher FC tend to attract more CO_2 emissions. Finally, population growth is another important factor that contributes to reducing CO_2 emissions, with a strong negative correlation between population growth (PGR) and CEs, with a correlation value of −0.78. A correlation between agriculture land (AGLA) and CEs also exists, with a correlation value of −0.78 showing that countries with more AGLA tend to minimize their CO_2 emissions [Fig. 2].

The time series plot illustrated in Fig. 3 depicts the trend in CO_2 emissions over time, from 1971 to 2020. The plot shows that CO_2 emission has fluctuated over time, with both positive and negative values. From the mid-1971s to the early 1980s, CO_2 emission was comparatively low, with values mostly between 0.042 and 0.083 (metric tons per capita). In the mid-1995s, CO_2 emission started to rise steadily, with values increasing to over 0.140 (metric tons per capita) by the late 1995s. The plot shows that CO_2 emissions significantly increased in the early 2000s, reaching a peak of approximately 0.167 (metric tons per capita) in 2000. From the graph, it can be seen that Bangladesh's overall CO_2 emissions have been rising year over year since 2001, reaching a peak in 2020 of 0.581 (metric tons per capita). There was a sharp increase trend from 2002 to 2020 [Fig. 3].

Linear models can be used to generate predictions about the dependent variable and can be used to estimate the impact of changes in the independent variables on the dependent variable. Multiple linear regression coefficients with their statistical significance are calculated, and the summary analysis of the multiple linear regression model is shown in Table 2.

It is observed that the variables population growth, industry value added, electricity production from oil, total number of motor vehicles, and manufacturing value added are statistically significant with *p*-values. This implies that these variables are important predictors of the target variable. On the other hand, the variables GDP, electricity production from gas, agriculture land, and fertilizer consumption are not statistically significant with p-values above the threshold of 0.05. This indicates that there is not enough evidence to suggest that these variables are causal. It is noticeable that the VIF values range from 2.33 to 196.05, so, multicollinearity is suspected. To check the multicollinearity, we draw a VIF plot that is shown in Fig. S1. Based on the VIF plot, we can see that MVG, TNRMV, EPOS, EPGS, and IVG variables have VIF values greater than the threshold value of 10, which suggests that there is strong multicollinearity between these variables and other independent variables in the regression model [42]. This could lead to inaccurate parameter estimates and reduced model performance, and a linear model is not suitable for the data. To find the significant variables, we are applying stepwise regression and finding that the variables population growth, industry value added, electricity production from oil, total number of motor vehicles and manufacturing value added variables are significant for the data. On the other hand, there are several approaches to handling multicollinearity in a regression analysis. To deal with multicollinearity, we first use scatterplots and line plots to examine the linear relationship between the experimental variable and other selected variables. Fig. 4 represents the scatterplots and 95 % confidence interval of three models and other selected variables with CO_2 emission.

In Fig. 4, we can see that all covariates are not linearly associated with the experimental variable. A nonlinear or nonparametric model may be more suitable to capture the complex relationship [43]. Nonparametric models don't assume a particular functional form for the relationship between variables, giving them more flexibility, while nonlinear models can handle nonlinearity. Applying a

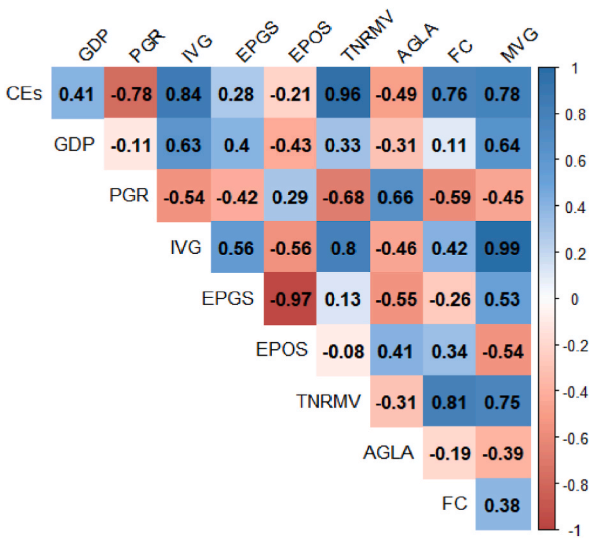

Fig. 2. Correlation matrix.

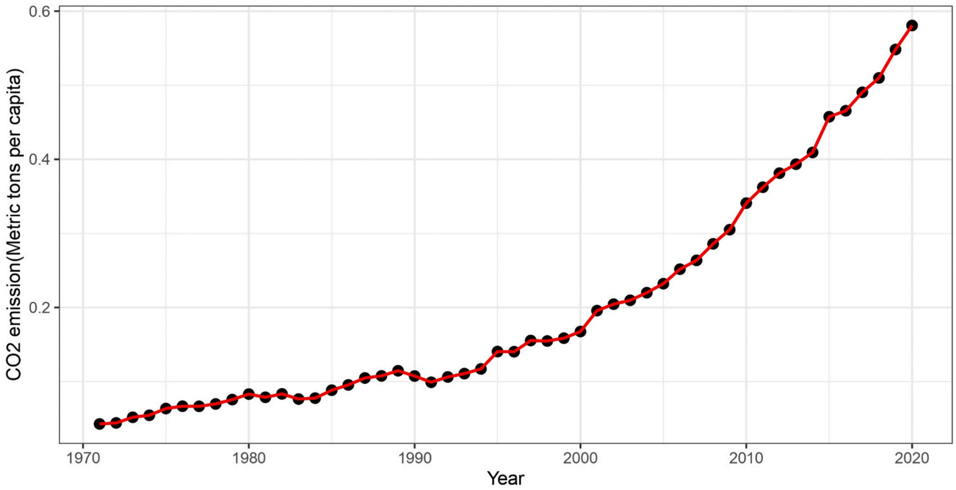

Fig. 3. Time Series Plot for CO_2 emission.

Table 2
Estimation of the multiple linear model.

Variable	Estimate	Std. Error	t-value	p-value	VIF
Intercept	−0.162	0.208	−0.78	0.44	–
GDP (annual growth)	0.00102	0.0012	0.83	0.41	2.33
Population growth	−0.0542	0.0147	−3.68	< 0.001***	7.61
Industry value added	0.0364	0.0072	5.04	< 0.001***	196.1
Electricity production from gas	0.00353	0.0014	2.52	< 0.05*	29.98
Electricity production from oil	0.000839	0.00089	0.95	0.35	28.66
Total no. Of motor vehicles	0.00438	0.0014	3.10	< 0.01**	28.30
Fertilizer consumption	0.000036	0.00197	0.02	0.98	3.80
Agriculture land	0.00683	0.00567	1.20	0.24	7.73
Manufacturing value added	−0.0359	0.0082	−4.36	< 0.001***	99.26

Note: p-value $< 0.001,^{***}, 0.01 < \text{p} < 0.05,^{**}, 0.05 < \text{p} < 0.1,^{*}$.

nonlinear or nonparametric model to our data will help us solve the issue. To determine whether the response variable exhibits non-linearity to the covariates when using the non-linear and nonparametric model. To test this, we will plot our response variable, CO_2 emission, against each covariate we have chosen, and we will construct a linear model, a polynomial model, and a GAM model based on that data. It is clear from Fig. 4 that the majority of covariates are appropriate for fitting non-linear and non-parametric regression for this data. Apply quadratic polynomial regression without interaction to the dataset with selected variables, and to check the significance of the coefficients in the quadratic polynomial regression model, we perform a hypothesis test for each coefficient. We consider the following hypothesis,

$$H_0 : \beta_1 = \beta_2 = \ldots = \beta_{12} = 0, \text{i.e., polynomial regression model is not significant against}$$

$$H_0 : \beta_1 \neq \beta_2 \neq \ldots \neq \beta_{12} \neq 0, \quad \text{indicated that the polynomial regression model is significant.}$$

Findings revealed that the variables GDP, PGR, IVG, EPOS, TNRMV, AGLA, and MVG have very small *p*-values (all less than 0.05), indicating that each source of variation explains a significant amount of variability in the response variable. Additionally, the *F*-values for each source of variation are quite large relative to their degrees of freedom, further supporting the conclusion that each source of variation is statistically significant [Table S2].

Polynomial regression can be sensitive to outliers as well as may overfit the data, on the other hand, GAM is less sensitive to outliers and does not overfit the data as easily. Therefore, it is evident that the most appropriate model for the data is one that integrates variables based on their kind of relationship, which entails a combination of linear and non-linear associations. The results of GAM are shown in Table 3.

Only the total CO_2 emissions and GDP were found to be insignificant in the non-linear part, whereas the rest of the variables have been identified as significant. Therefore, the multicollinearity issue with the linear model is resolved by this model. In the first column of the above table, these covariates' estimated values are provided. The degree of a curve's nonlinearity is indicated by the effective

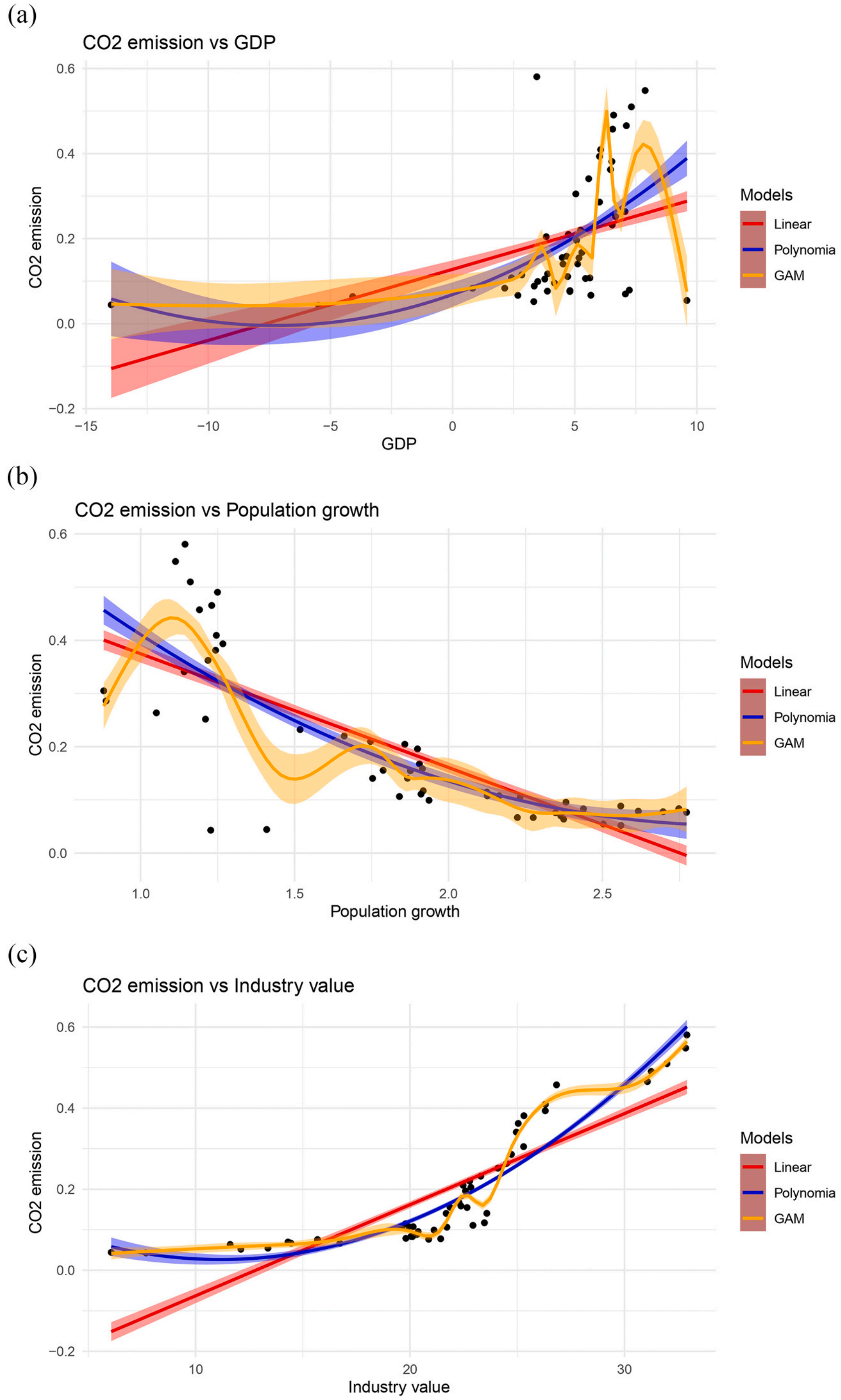

Fig. 4. Fitting of different models for CO_2 emission against (a) GDP, (b) population growth, (c) industry value, (d) population from oil, (e) production from gas, (f) agricultural land, (g) motor vehicles, (h) fertilizer consumption, and (i) manufacturing value.

degrees of freedom (edf), a summary statistic used in GAM [38]. If the edf value is equal to one, it denotes a linear relationship; if it is between one and two, it refers to a weakly non-linear relationship; and if it is greater than two, it suggests a very non-linear relationship with regard to the variable. The edf and reference degrees of freedom are important measures of goodness of fit. The bottom figure includes degrees of freedom as a reflection of these. Most of the edfs are extremely close to the reference df, and several of them are equal suggesting a very good model fit [Table 3].

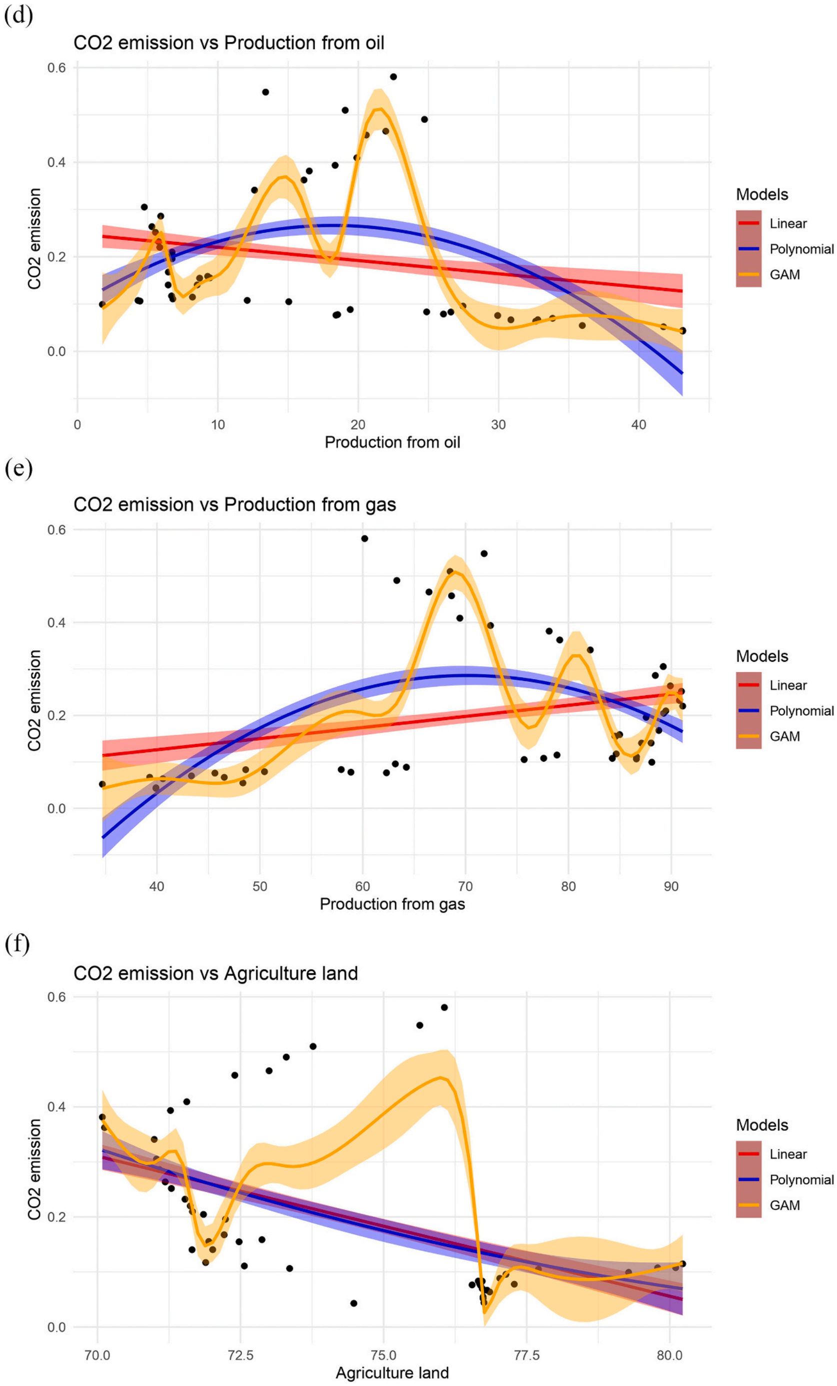

Fig. 4. (*continued*).

According to Wood (2017), one way for determining the adequacy of a smooth's basis dimension is to estimate the residual variance by comparing residuals that are close neighbours with respect to the smooth's (numeric) variables [38]. Each of these plots provides a distinct view of the model residuals. The results of the initial, insufficiently fitted model are shown in Fig. S2. In the top-left corner, a Q-Q plot compares the model residuals to a normal distribution. A good-fitted model will have almost linear residuals. In comparison, the plot has a straight line. In the top-right corner, a residual histogram can be seen. This should be symmetrical and shaped like a bell. We now have an approximately bell-shaped histogram for our model. On the bottom-left corner, is a plot of the residual values. These should be symmetrical around 0, but the values in our model are dispersed across the place. On the bottom right, you can see the response plotted against the fitted values. A perfect model provides a straight line. We cannot anticipate a perfect

(g)

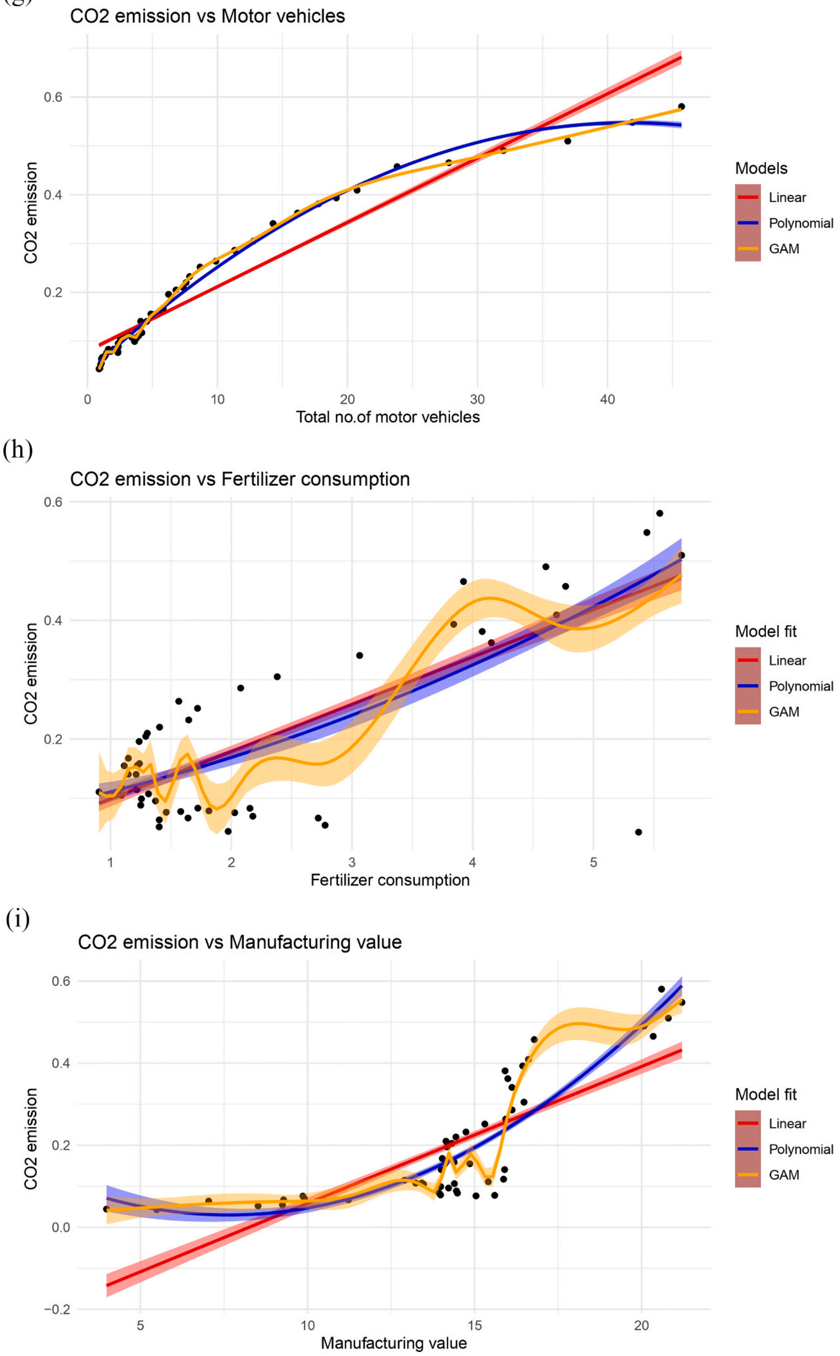

Fig. 4. (*continued*).

model, but we do believe that the pattern will move closer to the 1-to-1 line. It is observed that the histogram is nearly bell-shaped, the Q-Q plot, and the response vs. fitted values comparison clusters around a 1-to-1 line. All of them show a substantially better model fit [Fig. S2].

In order to determine which regression model is best, we compare three regression models i.e., polynomial regression model, MLR model, and GAM model. The models will be evaluated according to the RMSE, MSE, R-squared, AIC, BIC, variance (sigma), value of each model and it is showed in Table S1.

Three different models are compared based on various performance metrics that assess the models' overall predictive power and goodness of fit to the data and results are presented in Table S1 and Fig. 5. The GAM has the lowest MSE and highest R^2 value of 0.996,

Table 3
Results of GAM model.

Approximate significance of linear terms					
Coefficients	Estimate		Std.Error	t value	p-value
Intercept	0.095		0.016	5.93	< 0.001***
TNRMV	0.0115		0.00174	6.59	< 0.001***
Approximate significance of smooth terms					
	Estimates	Effective degrees of freedom	Reference degrees of freedom	F	P-value
s (GDP)	−0.0215 −0.00447	1.17	1.31	1.34	0.25
s (PGR)	−0.0299 −0.0121	1.81	1.96	6.54	< 0.001***
s (IVG)	0.272 0.129	2.00	2.00	10.02	< 0.01**
s (EPGS)	−0.00484 0.0266 0.0104 0.0252	1.16	1.28	4.28	< 0.001***
s (EPOS)	0.022 0.054	3.92	3.99	7.37	< 0.001***
s (AGLA)	0.00835 0.00551 −0.037 −0.00732	3.05	3.54	4.02	< 0.05*
s (FC)	0.0219 −0.0221	1.97	1.99	8.98	< 0.001***
s (MVG)	−0.166 −0.139	1.04	1.08	5.58	< 0.05*
Performance indicator	R-squared = 0.996; RMSE = 0.008; MSE = 0.000063; AIC = −303.21; BIC = −266.64				

Note: p-value < 0.001,***, 0.01 < p < 0.05,**, 0.05 < p < 0.1*..

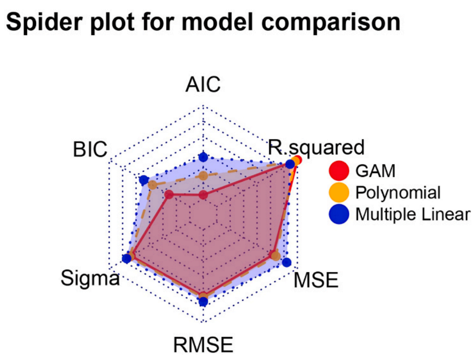

Fig. 5. Spider plot of model comparison.

indicating that it fits the data extremely well. It also has the lowest AIC and BIC values, which are indicators of the model's complexity and overall fit to the data. The RMSE for this model is 0.008, which is a measure of the average difference between the predicted values and actual values. The sigma value is 0.011, which is a measure of the standard deviation of the residual. We are interested in creating a spider plot to compare the three models graphically. It is a graphical representation of data that displays multiple model criteria on a two-dimensional plan. A visual comparison of the three models is shown in Fig. 5. The spider plot presented in Fig. 5 compares the performance of three different regression models: GAM Regression, Polynomial Regression, and Multiple Linear Regression. Each spoke in the plot indicates a different performance metric, and the length of each spoke corresponds to the value of that metric for each model. From the plot, we can see that the GAM Regression model has the highest R^2 value and the lowest RMSE value, indicating that it is the best performing model overall. The Generalized Additive model appears to perform better than the other two models in terms of MSE, R^2, AIC, BIC, RMSE, and sigma values, making it the best model for this dataset, according to the comparison.

The authors predict the CO_2 emissions along with the 95 % confidence interval (CI) using the finally selected GAM model. Fig. 6 contrasts the actual and fitted values for Bangladesh's total CO_2 emissions calculated using the GAM model with the 95 % CI.

We can plot a time series with a 95 % CI to better understand CO_2 emission trends and the performance of the GAM model. The fitted line shows the expected values based on the model that was fitted to the data, while the observed data line shows the actual

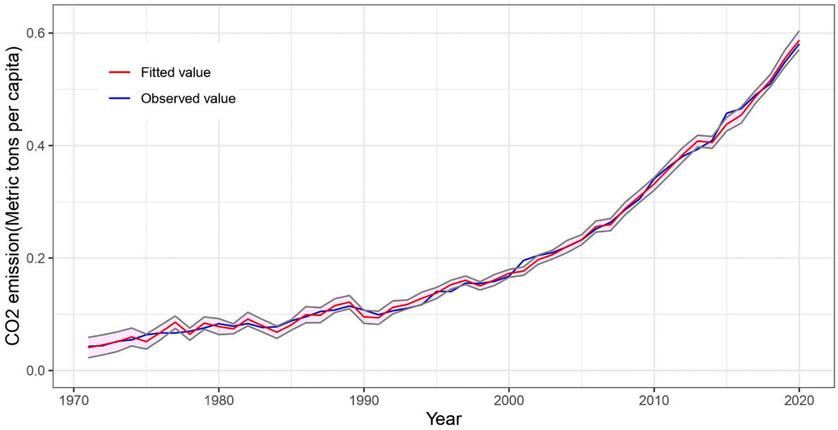

Fig. 6. Prediction with a 95 % Confidence interval of CO_2 emissions in Bangladesh.

values that were observed in time. The confidence interval, which is based on the uncertainty in the model and the data, depicts the range of values within which we can determine with a certain level of confidence that the true values lie. We can be 95 % confident that the true value for that year falls within the range provided by the 95 % CI. The plot shows that the CO_2 emissions value is generally positive and upward trend, with some fluctuations in between. Overall, almost all of the fitted values are within the confidence level, which provides us with enough evidence to conclude that the GAM model provides an appropriate estimation [Fig. 6].

4. Discussion

The study's primary goal was to identify the influential variables of CO_2 emissions using World Bank data, but this was impossible without a suitable model. However, we observed non-linearity in the data, so we chose a model that could appropriately identify the determinants and explain the type of relationship between the covariates and the response variable using the Generalized additive model. The long-term CO_2 emissions are significantly and positively affected by the transportation, industrial, and electricity sectors. According to the findings, an increase in transportation, industrialization, and non-renewable energy consumption in Bangladesh is accompanied by a decline in sustainability environment. The study is consistent with other research in Bangladesh [18,44–47], which verified the positive relationship between electricity, industrial, transportation and CO_2 emissions. Furthermore, this research explores Bangladesh's potential for utilizing sources of renewable energy to achieve sustainable environment. Findings depic that non-renewable energy usage seems to have a critical role in rising CO_2 emissions in Bangladesh. The findings show that boosting renewable energy sources while decreasing nonrenewable energy sources in the overall energy mix can help to lessen CO_2 emissions in Bangladesh since nonrenewable energy consumption has a significantly positive impact on CO_2 emissions. This finding is supported by previous studies [48–50]. Using renewable sources of energy for the generation of energy is vital for achieving environmental sustainability and mitigating climate change, which has become an important issue [51]. As global environmental consciousness grows, Bangladesh has to shift its energy balance to a system based primarily on renewables in order to promote the use of sustainable energy sources and contribute to the creation of an environmentally healthy ecosystem.

This research reveals a significant positive connection between chemical fertilizer use, agriculture, and CO_2 emissions in Bangladesh, indicating that decreasing agricultural production eventually increases CO_2 emissions. Instead, while agriculture and forests capture CO_2 from the atmosphere and store it as biomass carbon, agricultural productivity improves the quality of the environment which is comsistent with other studies [52–55]. However, agriculture's contribution to Bangladesh's GDP has been reducing over time as a result of industrialization [56]. According to the results of this study, conventional methods of agriculture should be improved by including contemporary technology to increase agricultural production, reduce CO_2 emissions, and ensure food security for Bangladesh's increasing population. Recently, several multinational organizations have developed the climate-smart agriculture (CSA) strategy [57], which modifies the expansion of agriculture to mitigate environmental damage. These leads will contribute to the long-term reduction and mitigation of climate change worldwide. The agricultural industry may be able to assist in decreasing greenhouse gas emissions by employing proper farming practices. A decline in carbon footprint can be achieved by absorbing the carbon released by agricultural operations using proper management and technology implementation.

5. Strengths and limitations

This study is focused on a comparative study between linear and non-linear models for predicting the CO_2 emissions in Bangladesh which offering the novelty in the literature. The CO_2 emissions will be influenced by other factors that may not be included in this study. Moreover, some other techniques, e.g., auto-regressive distributed lag (ARDL) model maybe useful in a future study for making a comparison with the GAM. Additionally, the cutting-edge ML/AI algorithms would be useful to design a further study on this topic.

6. Recommendation

The study's findings suggest that Bangladeshi authorities develop an environmental policy that cuts CO_2 emissions without jeopardising economic growth. In this regard, we recommend Bangladesh's government consider the implementation of carbon capture and storage technology to reduce CO_2 emissions from the use of fossil fuels in industry and the production of electricity. Clean environmental items such as photovoltaic solar cells, wind turbines, and hydro turbines may be duty-free and encouraged for everybody. Another idea is to evaluate current carbon tax legislation while looking for better energy sources for Bangladesh's transport sector. Emissions of CO_2 can be significantly decreased by using fewer fossil fuels such as kerosene, natural gas, and diesel oil. Bangladesh, as a developing country, must adopt a solid environmental policy that applies to all economic sectors, including industrial, shipbuilding, chemical manufacturing, and leatherworking. Furthermore, the utilisation of renewable energy in all economic activity requires institutional alignment to ensure long-term economic growth. Finally, increased monitoring of environmental damage, undertaking ecologically friendly initiatives, and reducing the fraction of non-renewable energy in overall energy use can all help to reduce environmental damage without limiting Bangladesh's economic growth.

7. Conclusion

The authors attempted to utilize a non-parametric model (Generalized Additive Model) to develop a non-linear model from the visual depiction that the response variable (CO_2 emissions) exhibits strong non-linear associations with the covariates. In the proposed approach, three regression models are first employed to create and predict outcomes from CO_2 emissions and other relevant indicators data, and these models are then evaluated using various criteria (MSE, R-squared, AIC, BIC, RMSE, and Sigma). Among the three models (multiple linear regression, quadratic polynomial regression, and Generalized additive model), the GAM model gives better performance.

Funding

All authors ensure that this research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data availability

This study is based on the secondary dataset. The World Development Indicators database of the World Bank provided the secondary data, which is accessed through the following link: https://data.worldbank.org/country/BD. Additionally, information about the total number of registered motor vehicles may be found at the Bangladesh Road Transport Authority website http://www.brta.gov.bd.

CRediT authorship contribution statement

Ruhul Amin: Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Md Sifat Ar Salan:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Md Moyazzem Hossain:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors are grateful to the World Bank and Bangladesh Road Transport Authority for providing the datasets for this analysis. The authors would like to express their gratitude to the three reviewers and Academic Editor for their valuable comments and feedback which helped to improve the quality of the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e25416.

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