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Abstract: With population and income growth, the need for energy has increased in developing and emerging economies, which has inevitably led to an increase in carbon dioxide emissions (CO_2e). This paper investigates the impact of energy consumption on CO_2e influenced by population growth, energy consumption per capita, and income. In particular, this paper investigates whether or not an increase in energy consumption, energy intensity, energy consumption per capita, population growth, and income impacts CO_2e in China, India, and the USA. The study applied the non-linear Autoregressive distributed lag (NARDL) and machine learning techniques. We found a significant impact of energy consumption per capita on the CO_2 emissions in China, India, and USA. Furthermore, the results revealed that, when income increased, CO_2 emissions increased in India, but decreased in the USA. The results confirmed that population growth increases CO_2 emissions only in India. The results revealed that a decrease in energy intensity significantly improves the environmental quality in China and India. Finally, we forecasted the CO_2e trend from 2017 to 2025. The results revealed an upcoming increase in CO_2e levels in China and India. Conversely, the forecasted results demonstrated a downward trend of CO_2e emissions in the USA.

Keywords: energy consumption; CO_2 emission; NARDL; machine learning models; China; India; USA

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1. Introduction

Climate change and global warming have been acute problems for a few decades. They have led to the continuity of severe economic, social, and environmental issues, particularly endangering human health. Scholars and scientists have argued that anthropogenic activities harm the environment [1,2]. Many research results have confirmed that energy consumption (EC) directly or indirectly affects the environment [3]. Furthermore, it has been observed that recent developments in the industrial sectors of many developing and emerging economies have been accompanied by the use of contaminated fuels, resulting in increased global warming, particularly leading to a rise in CO_2e levels. CO_2e has crossed a point that has not been seen in thousands of years. According to the International Energy Agency (IEA) estimations, CO_2e emissions were projected to rise by 4.8% in 2021 due to the high demand for oil, coal, and gas [4]. The consequences of hazardous pollutants are linked to the environment, social development, and human health. Many studies have reported that CO_2e causes environmental degradation. These hazardous pollutants produce many respiratory diseases, damage the lungs, and increase economic expenditure [5,6]. In parallel with these consequences, CO_2e impacts domestic and international trade. Overall, CO_2e emissions have consistently been a significant discussion and concern among policymakers and government personnel [7–9]. Therefore, their reduction holds paramount importance for the betterment of society and the environment. Analyzing energy consumption and its impact on CO_2e is crucial in reshaping policies related to factors influencing CO_2e emissions.

The escalating levels of CO_2e can primarily be attributed to anthropogenic activities, wherein human-induced emissions of greenhouse gases exert a significant influence. Given the ongoing transition to a low-carbon economy, it is imperative to conduct a comprehensive assessment of the intricate interplay between energy consumption, energy intensity, and population dynamics, and their collective implications on the environment [10,11]. Consequently, urbanization, which involves an increasing concentration of the population in urban areas, has been identified as a primary cause of EC [12]. As populations grow and people migrate from rural to urban regions, the demand for resources and infrastructure also escalates, leading to significant environmental impacts. The rapid pace of urbanization is particularly evident in industrial and emerging economies, where the pursuit of faster economic growth has prompted substantial shifts in living standards [13]. This development has increased income growth [14] and infrastructure; as a result, EC has risen dramatically.

According to the IEA, oil, natural gas, and coal accounted for 40.8%, 16.2%, and 10% of global EC in 2018, which can be considered the primary cause of CO_2e [15]. China, India, and USA account for 40.42% [16] of the global population; they have a significant geographical and social impact on the overall environment. Moreover, these countries have experienced rapid economic growth, leading to changes in population distribution and economic activities, requiring additional EC to meet household and commercial demands. Considering that China, India, and the USA are among the world's largest CO_2 emitters and energy consumers, they present valuable case studies for policymakers to analyze the intricate relationship between EC, energy consumption per capita (ECPC), energy intensity (EI), and CO_2e emissions. The EC of China, India, and the USA primarily depends on coal, petroleum, oil, and natural gas. In China, 78% of its total EC is based on coal and petroleum [17]. India generates 66% of its electricity from coal and petroleum. Similarly, the USA's EC is primarily based on petroleum (35%), natural gas (34%), renewable energy (12%), and nuclear power (9%). These statistics show that world's population is engulfed in air pollution due to hazardous pollutants.

Overall, the drivers related to EC, such as energy fuels and the demographic and economic factors of these countries, have been important for stimulating EC. In this regard, plenty of previous research has focused on the association between EC, economic growth, gross domestic product, and CO_2e. Furthermore, the evidence on the association between EC, income, and CO_2e in the recent scholarly literature has shown that this topic is the most recent and needs special attention. Ref. [18] reviewed an asymmetric analysis of the impact of EC on CO_2e using data collected between 1965 to 2019 for G7 countries. The findings revealed a significant influence on the outcome variable, ecological footprint. Additionally, the research results showed a bidirectional and unidirectional asymmetrical causality among these countries. In addition, other scholars, such as [19], attempted to find the causal relationship between EC, ECPC, urban population, and CO_2e. Their findings reported that EC positively impacts CO_2e. The study conducted by [20] noted that natural gas and petroleum have an asymmetric impact on CO_2e. Regarding EI, economic growth, and CO_2e, Ref. [10] empirically tested the effect of EI and economic growth on

CO_2e. The results confirmed that EI promotes CO_2e; however, the findings revealed a negative association between economic growth and CO_2e, while renewable energy was found to be helpful in mitigating CO_2e. In line with these results, the findings in the study [21,22] also confirmed that a higher EI promotes CO_2e. Infrastructure, construction, and development in urban areas also stimulate EC to meet public and business energy demands [12]. Additionally, rapid population growth influences environmental quality, such as population size in regard to CO_2e [23,24]. Ref. [25] attempted to examine the influence of EC, population growth, and GDP growth on CO_2e over a period between 1970 and 2009. The results revealed that per capita GDP and EC positively impact CO_2e.

Apart from econometrics and statistical techniques, previous studies have applied machine learning models to analyze data, make predictions, and extract insights. ML learns data based on previous records and has a predictive capability to find patterns, which is not possible using traditional methods. ML algorithms analyze patterns, draw valuable insights from data, and solve complex problems. ML algorithms deal with complex issues and are prevalent in forecasting. For instance, Ref. [26] suggested that an artificial neural network (ANN) predicts better than other traditional models. Other studies, for example, Ref. [27], used nine factors to predict the CO_2e in China, India, Brazil, Australia, and the USA. The findings showed that ANN had a better-predicted capability. Apart from ANN, support vector machines (SVM) and long-short-term memory (LSTM) are popular in prediction and forecasting-related problems [7,28,29].

Existing studies have undoubtedly highlighted the association among EC, industrialization, economic development, urbanization, population, and environmental pollution; however, most existing studies either cover a large study sample or target a single-country analysis. Existing studies lack comprehensive investigations into the relationship between EC, EI, and environmental pollution. More specifically, thorough analyses of the relationship between EC and CO_2e, influenced by the growing population and ECPC, are scarce in the current studies. This study assesses the effect of EC, EI, ECPC, income, and population on the CO_2e in China, India, and the USA. In particular, this study evaluates whether or not an increase in EC, EI, ECPC, income, and population affects CO_2e. Furthermore, this paper identifies which input factor has a more significant effect on CO_2e. Third, this study applies advanced machine learning (ML) techniques for predicting the forthcoming trend of CO_2e in China, India, and the USA, which is a pivotal step in analyzing its environmental consequences on society. The outcomes based on the empirical evidence would be helpful for policymakers to address how an increase in population growth and ECPC accompanied by EC interact with CO_2e. Further, the study provides policy suggestions for taking the necessary action to avoid the increasing trend of EC with fossil fuels.

This study used five inputs, EC, EI, ECPC, income, and population growth, and one output variable (CO_2e) and employed a dataset with time series samples collected between 1980 and 2016 for the three countries, China, the USA, and India. This paper uses a combination of NARDL and ML algorithms, such as ANN, SVM, and LSTM. This study contributes from theoretical and practical perspectives, presents a robust model of the association between EC and CO_2e, and assesses its environmental consequences.

The following structure is used to organize the paper. The following section (Section 2) will describe this study's research approach and data collection methods. The subsequent section (Section 3) will present and analyze the gathered data, while Section 3 will interpret the study's findings. Finally, the paper will conclude by summarizing the main findings, discussing their implications.

2. Methodology

2.1. Dataset

In this study, we used five input variables: EC, EI, ECPC, income, and pollution growth, as input indicators for CO_2e in China, India, and the USA. This study used time series data for China, India, and the USA. The data on EC are expressed in quad BTU. The data on ECPC and EI are expressed in KWh and KWh per USD respectively. This study used GDP per capita (current USD) as an income indicator. The population growth is expressed as the annual % of the total population. Finally, the output variable, CO_2e, is expressed in kt. The data for this paper were acquired from reliable sources [30–32].

2.2. NARDL Model

This study used the NARDL model to find the impact of the explanatory variables on the CO_2e in China, India, and the USA. The NARDL model is useful because it assesses the positive and negative impacts of the variables on the outcome variable in both the short and long term. Furthermore, NARDL allows for the simultaneous use of non-linear asymmetries and co-integration in a single equation, and can be performed on a small sample.

The following equation examines the long-term association between CO_2e, EC, ECPC, EI, and population growth.

$$CO_{2t} = \beta_o + \beta_1 EC + ECPC + EI + IN + PG + \varepsilon_t \tag{1}$$

CO_2, EC, ECPC, EI, IN, and PG represent CO_2 emissions, energy consumption, energy consumption per capita, energy intensity, income, and population growth, respectively. ε_t represents an error term, while β_i is the long-term co-efficient. Following the recent studies [33–35], Equation (1) can be rewritten for the long-term specification of CO_2e.

$$\begin{aligned} CO_{2t} = \delta_o + \delta_1\left(EC_t^+\right) + \delta_2\left(EC_t^-\right) + \delta_3\left(ECPC_t^+\right) + \delta_4\left(ECPC_t^-\right) + \delta_5\left(EI_t^+\right) \\ + \delta_6\left(EI_t^-\right) + \delta_7\left(IN_t^+\right) + \delta_8\left(IN_t^-\right) + \delta_9\left(PG_t^+\right) + \delta_{10}\left(PG_t^-\right) + \varepsilon_t \end{aligned} \tag{2}$$

where δ_s represents the co-efficient vectors, while EC, ECPC, EI, IN, and PG indicate the partial sum variations in EC, ECPC, EI, income, and population growth, respectively. Following [36], the positive and negative values of EC, ECPC, EI, IN, and PG can be represented as follows:

$$EC^+ = \sum_{i=n}^{t} \Delta EC_i^+ = \sum_{i=n}^{t} max(\Delta EC_i, 0) \tag{3}$$

$$EC^- = \sum_{i=n}^{t} \Delta EC_i^- = \sum_{i=n}^{t} min(\Delta EC_i, 0) \tag{4}$$

$$ECPC^+ = \sum_{i=n}^{t} \Delta ECPC_i^+ = \sum_{i=n}^{t} max(\Delta ECPC_i, 0) \tag{5}$$

$$ECPC^- = \sum_{i=n}^{t} \Delta ECPC_i^- = \sum_{i=n}^{t} min(\Delta ECPC_i, 0) \tag{6}$$

$$EI^+ = \sum_{i=n}^{t} \Delta EI_i^+ = \sum_{i=n}^{t} max(\Delta EI_i, 0) \tag{7}$$

$$EI^- = \sum_{i=n}^{t} \Delta EI_i^- = \sum_{i=n}^{t} min(\Delta EI_i, 0) \tag{8}$$

$$IN^+ = \sum_{i=n}^{t} \Delta IN_i^+ = \sum_{i=n}^{t} max(\Delta IN_i, 0) \tag{9}$$

$$IN^- = \sum_{i=n}^{t} \Delta IN_i^- = \sum_{i=n}^{t} min(\Delta IN_i, 0) \tag{10}$$

$$PG^+ = \sum_{i=n}^{t} \Delta PG_i^+ = \sum_{i=n}^{t} max(\Delta PG_i, 0) \tag{11}$$

$$PG^- = \sum_{i=n}^{t} \Delta PG_i^- = \sum_{i=n}^{t} min(\Delta PG_i, 0) \tag{12}$$

Finally, by substituting Equation (2) to Equation (12) into Equation (1), the following NARDL model can be formulated.

$$\begin{gathered}\Delta CO_{2t} = \vartheta_o + \vartheta_1 CO_{2t-1} + \vartheta_2^+\left(EC_{t-1}^+\right) + \vartheta_3^-\left(EC_{t-1}^-\right) + \vartheta_4^+\left(ECPC_{t-1}^+\right) + \\ \vartheta_5^-\left(ECPC_{t-1}^-\right) + \vartheta_6^+\left(EI_{t-1}^+\right) + \vartheta_7^-\left(EI_{t-1}^-\right) + \vartheta_8^+\left(IN_{t-1}^+\right) + \vartheta_9^-\left(IN_{t-1}^-\right) + \\ \vartheta_{10}^+\left(PG_{t-1}^+\right) + \vartheta_{11}^-\left(PG_{t-1}^-\right) + \sum_{i=1}^k \omega_i \Delta CO_{2t-i} + \sum_{i=0}^k \varsigma_{2i}^+ \Delta EC_{t-i}^+ + \\ \sum_{i=0}^k \varsigma_{3i}^- \Delta EC_{t-i}^- + \sum_{i=0}^k \varsigma_{4i}^+ \Delta ECPC_{t-i}^+ + \\ \sum_{i=0}^k \varsigma_{5i}^- \Delta ECPC_{t-i}^- + \sum_{i=0}^k \varsigma_{6i}^+ \Delta EI_{t-i}^+ + \sum_{i=0}^k \varsigma_{7i}^- \Delta EI_{t-i}^- + \sum_{i=0}^k \varsigma_{8i}^+ \Delta IN_{t-i}^+ + \\ \sum_{i=0}^k \varsigma_{9i}^- \Delta IN_{t-i}^- + \sum_{i=0}^k \varsigma_{10i}^+ \Delta PG_{t-i}^+ + \sum_{i=0}^k \varsigma_{11i}^- \Delta PG_{t-i}^- + \varepsilon_t\end{gathered} \quad (13)$$

where ϑ's represents the co-efficient of the long-term positive and negative changes in EC, ECPC, EI, INC, population growth, and CO_2e. The NARDL model requires various tests and assumptions; also, it requires the model specification. For instance, this model requires that the variables are not accepted at the second difference. Second, it is also important to confirm whether the variables are co-integrated and have a long-term association, such as $H_o : \vartheta_1 = \vartheta_2 = \vartheta_3 = \vartheta_4 = \vartheta_5 = \vartheta_6 = \vartheta_7 = \vartheta_8 = \vartheta_9 = \vartheta_{10} = \vartheta_{11}$, showing that the variables have no existence of a long-term relationship; alternatively, the hypotheses claim, $H_1 : \vartheta_1 \neq \vartheta_2 \neq \vartheta_3 \neq \vartheta_4 \neq \vartheta_5 \neq \vartheta_6 \neq \vartheta_7 \neq \vartheta_8 \neq \vartheta_9 \neq \vartheta_{10} \neq \vartheta_{11}$. After confirming that the data are stationary, the long-term associations, and the robustness tests, we can proceed with the next step of analyzing the trend of variables for the short-term and long-term co-integration analysis.

3. Results and Discussion

This study adopted the NARDL and machine learning models (LSTM, ANN, and SVM). The NARDL model can examine both short-term and long-term relationships, and in particular, it captures the immediate impact of changes in independent variables (short-term dynamics), as well as long-term equilibrium relationships (long-term dynamics). Unlike other regression models that may require many observations, NARDL models can provide reliable results even with limited data. On the other hand, machine learning models, particularly the ANN, LSTM, and SVM models, are more popular and advanced than traditional models. For instance, Naive Bayes classifiers assume feature independence, which is not always realistic. Although they exhibit computational efficiency and perform effectively in specific domains, such as text classification, they may not adequately capture the intricate relationships between features. Simple linear regression models are susceptible to the impact of outliers, which refer to data points that significantly deviate from most of a dataset. These outliers have the potential to exert a substantial influence on the slope and intercept of the linear regression line. Consequently, this can result in distorted and less dependable predictions. In contrast, advanced machine learning models, such as ANN algorithms, are widely recognized as a popular and influential technique that emulates the functioning of a biological nervous system. Using ANN, acquiring knowledge of intricate patterns and making predictions for non-linear and complex problems within a reasonable timeframe is possible. SVM leverages computational and statistical learning methods to handle various parameters, including quadratic, radial, neural, epsilon, kernel functions, and C values. By employing this technique, it becomes feasible to minimize the errors originating from the training data while preserving the integrity of the decision boundary structure.

3.1. Summary of Unit Root Tests (NARDL Model)

This study used ADF and PP unit root tests to analyze the stationary time series data for China, India, and the USA. ARDL and NARDL models can be applied when all the variables are stationary at the level and first difference. Thus, checking how stationary the variables are is an important step before proceeding with the ARDL or NARDL model. As this study is interested in checking the explanatory variables' positive and negative impacts and long-term impacts on CO_2e, we applied the NARDL model to interpret the results. Table 1 presents the results of the ADF and PP unit root tests. Table 2 highlights the BDS test results, which show a non-linearity in EC, ECPC, EI, income, population growth, and CO_2e in China, India, and the USA. Thus, the null hypothesis of the linearity of the data is rejected, as shown in Table 2.

Table 1. Unit root tests.

Country	**Variables**	**PP (Level)**	**PP (First Deference)**	**ADF (Level)**	**ADF (First Deference)**
China	CO_2e	−0.797	−3.865 **	−0.191	−3.964 **
	EC	−0.689	−3.208 **	0.326	−2.983 **
	ECPC	−0.861	−3.326 **	0.232	−3.519 **
	EI	−1.769	−3.478 **	−1.322	−3.218 **
	IN	0.259	−3.438 **	1.229	−3.510 **
	PG	−0.861	−3.518 **	−0.470	−3.309 **
India	CO_2e	0.689	−6.831 *	−0.686	−6.785 *
	EC	−1.815	−6.931 *	−1.805	−6.752 *
	ECPC	−0.010	−6.496 *	−0.013	−6.442 *
	EI	−1.125	−5.142 *	0.328	−5.318 *
	IN	1.249	−5.358 *	1.128	−5.398 *
	PG	−1.435	−2.963 **	1.365	−3.451 **
USA	CO_2e	0.187	−5.017 *	0.166	−5.007 *
	EC	1.594	−5.440 *	1.620	−5.331 *
	ECPC	−0.962	−5.256 *	−0.954	−5.209 *
	EI	−0.956	−4.271 *	6.769 *	−6.241 *
	IN	−3.655 **	−4.226 *	−6.711 *	−4.239 *
	PG	−0.646	−3.066 *	−1.653	−4.187 *

Notes: **, * = significant at 5% and 1%, EC = energy use, ECPC = EC per capita, EI = energy intensity, IN = income, and PG = population growth.

Table 2. BDS test.

Country		**CO_2e**	**EC**	**ECPC**	**EI**	**IN**	**PG**
China	2	0.183 ***	0.182 ***	0.185 ***	0.132 ***	0.184 ***	0.175 ***
	3	0.298 ***	0.295 ***	0.300 ***	0.193 ***	0.298 ***	0.296 ***
	4	0.367 ***	0.363 ***	0.370 ***	0.209 ***	0.369 ***	0.385 ***
	5	0.407 ***	0.402 ***	0.411 ***	0.226 ***	0.410 ***	0.448 ***
	6	0.424 ***	0.414 ***	0.428 ***	0.220 ***	0.426 ***	0.489 ***
India		CO_2e	EC	ECPC	EI	IN	PG
	2	0.198 ***	0.202 ***	0.195 ***	0.155 ***	0.168 ***	0.175 ***
	3	0.330 ***	0.338 ***	0.328 ***	0.254 ***	0.269 ***	0.281 ***
	4	0.419 ***	0.433 ***	0.417 ***	0.304 ***	0.323 ***	0.341 ***
	5	0.482 ***	0.501 ***	0.483 ***	0.323 ***	0.344 ***	0.373 ***
	6	0.524 ***	0.551 ***	0.530 ***	0.317 ***	0.334 ***	0.376 ***
USA		CO_2e	EC	ECPC	EI	IN	PG
	2	0.149 ***	0.195 ***	0.106 ***	0.192 ***	0.206 ***	0.114 ***
	3	0.250 ***	0.332 ***	0.150 ***	0.320 ***	0.348 ***	0.177 ***
	4	0.337 ***	0.428 ***	0.177 ***	0.407 ***	0.448 ***	0.199 ***
	5	0.388 ***	0.494 ***	0.177 ***	0.465 ***	0.520 ***	0.184 ***
	6	0.404 ***	0.536 ***	0.147 ***	0.502 ***	0.574 ***	0.176 ***

Note: Based on the residual values, *** rejects the null hypotheses at 1%.

3.2. Co-Integration Analysis

As this paper explores the long-term impact of the above-mentioned explanatory variables on CO_2e, to do so, the study examines the long-term equilibrium among the constructs. This study employs a bound test to confirm short- and long-term integration. Table 3 presents the results of the bound test with F statistics. The results indicate that the F-statistics values of China, India, and the USA lie above 10% of the critical values, confirming the long-term cointegration of the constructs.

Table 3. Bound test.

Country	F-Stat	Level	1st Difference	Decision
China	4.197 ***	1.99	2.94	Co-integration
India	12.19 ***	1.98	2.96	Co-integration
USA	3.207 ***	1.91	2.90	Co-integration

Note: *** indicates statistical significance at the 1% level.

3.3. NARDL Short-Term and Long-Term Co-Integration Analysis in China

After confirming the stationary nature and co-integration of the variables, we can identify the impacts of positive and negative shocks of EC, ECPC, EI, income, and population growth on CO_2e in China, India, and the USA. Table 4 presents the short-term and long-term co-integration results of China. As shown in Table 4, in the long term, positive shocks to ECPC harm CO_2e in China, such as a 1% increase in ECPC leading to an increase in CO_2e of 1.65%. The findings show that negative shocks to ECPC have a positive but insignificant impact on CO_2e in China. We found that positive shocks to EC have a negative but insignificant impact on CO_2e. In contrast, negative shocks decrease CO_2e by 2.59% for a 1% decrease in EC. Moreover, we found that positive and negative shocks to EI reduce CO_2e by 0.63% and 0.85%, for a 1% change in EI. Similarly, the findings show that a negative shock to income reduces CO_2e by 0.34% for a 1% decrease in INC. In the long term, the results indicate that negative shocks to population growth harm CO_2e (0.35%) for a 1% decrease in population growth.

Table 4. Long-term and short-term co-integration results of China (Dependent variable: CO_2e).

Variables	Coefficient	Std. Error	Prob.
Long-term co-integration results			
$ECPC^+$	1.655	0.062	0.000
$ECPC^-$	7.130	1.302	0.115
EC^+	−0.011	0.096	0.368
EC^-	−2.597	0.241	0.059
EI^+	−0.631	0.029	0.029
EI^-	−0.856	0.046	0.034
IN^+	−0.010	0.007	0.369
IN^-	−0.342	0.021	0.040
PG^+	0.023	0.011	0.287
PG^-	0.357	0.018	0.033
Short-term co-integration results			
$ECPC^+$	1.927	0.060	0.020
$ECPC^-$	10.911	0.932	0.054
EC^+	−0.161	0.052	0.200
EC^-	−1.583	0.072	0.029
EI^+	−0.509	0.029	0.036
EI^-	−1.521	0.056	0.023
IN^+	0.220	0.013	0.039
IN^-	−0.379	0.025	0.043
PG^+	−0.020	0.019	0.485
PG^-	0.297	0.014	0.031

In the short term, positive and negative shocks to ECPC increase CO_2e in China. Regarding EC, we found that, in the case of China, a decrease in EC improves the environmental quality in the short term. In addition, positive and negative shocks to EI reduce CO_2e significantly in China, while in the short term, positive shocks to income increase

CO_2e, and negative shocks to INC significantly reduce CO_2e in China. In the short term, the results indicate that negative shocks to population growth harm CO_2e (0.29%).

We also checked the CUSM and CUSM of the square tests. A CUSUM graph assesses the stability of the coefficients in a regression model. The red line in Figure 1 (China) and Figure 2 (China) shows the 5% significance level or the critical region, while the blue line shows the cumulative sum. As shown in the figures, the blue line lies within the 5% critical region, indicating that the residual variances are stable in China. Table 4 gives China's long-term and short-term co-integration results.

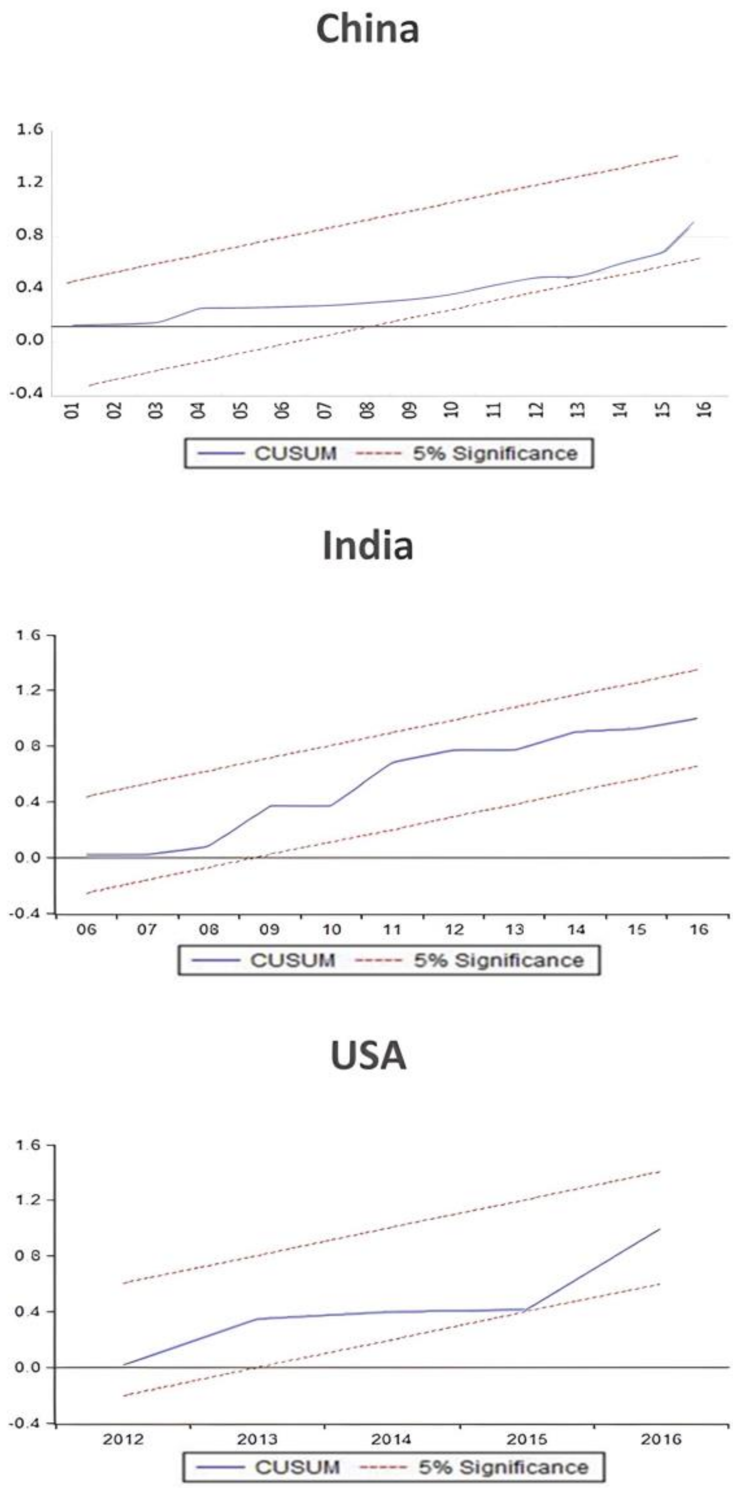

Figure 1. Cumulative Sum (CHINA, INDIA, and USA).

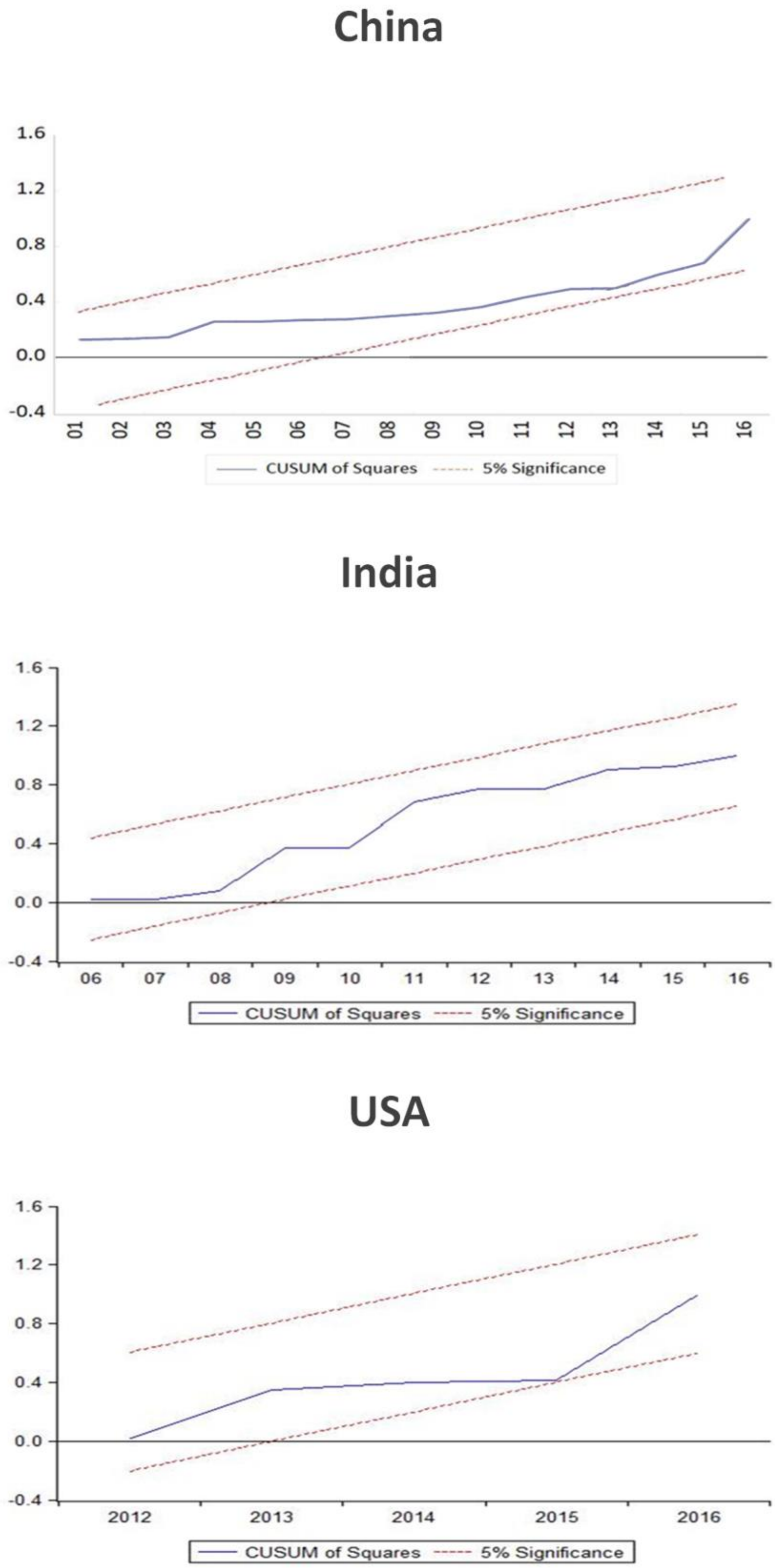

Figure 2. Cumulative Sum of squares (CHINA, INDIA, and USA).

3.4. NARDL Short-Term and Long-Term Co-Integration Analysis in India

The findings in the case of India show that positive shocks to ECPC reduce CO_2e by 5.92%. However, positive and negative shocks to EC in the long term increase CO_2e by 0.03% and 0.05% for a 1% change. Similarly, a 1% increase in EI increases CO_2e by 21.28%. The results revealed that a 1% increase in EI, income, and population growth improves

CO_2e by 21.28%, 5.29%, and 10.99%, respectively. The results in the short term for India revealed that ECPC significantly improves the environmental quality in India. Further, it was found that an increase in EC increases CO_2e by 0.016%. In addition, positive shocks to EI positively impact CO_2e in India. Regarding the income variable, the findings show that a negative shock to income reduces CO_2e, while positive shocks to population growth enhance CO_2e significantly. In the case of India, the CUSM and CUSM of the squares results indicate that the coefficients are stable. Table 5 gives India's long-term and short-term co-integration results, and Figure 1 (India) and Figure 2 (India) provide the results of the CUSUM and CUSUM of the squares.

3.5. NARDL Short-Term and Long-Term Co-Integration Analysis in USA

In the long-term co-integration for the USA, we found that a 1% increase in ECPC and EC increases CO_2e by 1.28% and 1.03%, respectively. However, negative shocks to ECPC and EC have no impact on CO_2e in the USA. Moreover, we found that negative shocks to EI reduce CO_2e by 0.66%. Similarly, a 1% increase in income reduces CO_2e by 0.63% in the USA. However, we found that positive and negative shocks to population growth have no impact on CO_2e in the USA. In the short term, positive and negative shocks to ECPC have no significant impact on CO_2e in the USA. Further, we found that negative shocks to EI significantly reduce CO_2e in the USA. Regarding EC, positive shocks improve CO_2e, while positive shocks to income and negative shocks to population growth reduce CO_2e in the short run. Additionally, the CUSM and CUSUM of the square results were found to be stable. Table 6 gives the USA's long-term and short-term co-integration results. Figure 1 (USA) and Figure 2 (USA) provide the CUSUM and CUSUM of the squares.

Table 5. Long-term and short-term co-integration results of India (dependent variable: CO_2e).

Variables	Coefficient	Std. Error	Prob.
Long-term co-integration results			
$ECPC^+$	−5.922	2.734	0.053
$ECPC^-$	−15.409	12.172	0.231
EC^+	0.033	0.004	0.000
EC^-	0.0552	0.029	0.089
EI^+	21.286	5.472	0.002
EI^-	1.125	3.250	0.735
IN^+	5.293	2.334	0.044
IN^-	1.144	0.644	0.103
PG^+	10.996	1.172	0.000
PG^-	2.881	2.758	0.318
Short-term co-integration results			
$ECPC^+$	−0.632	0.156	0.000
$ECPC^-$	−1.646	1.340	0.245
EC^+	0.016	0.005	0.017
EC^-	3.335	3.180	0.321
EI^+	3.213	0.822	0.002
EI^-	0.115	0.166	0.502
IN^+	−0.025	0.065	0.707
IN^-	0.770	0.134	0.000
PG^+	1.174	0.377	0.009
PG^-	0.307	0.377	0.431

Table 6. Long-term and short-term co-integration results of the USA (dependent variable: CO_2e).

Variables	Coefficient	Std. Error	Prob.
	Long-term co-integration results		
$ECPC^+$	1.289	0.587	0.064
$ECPC^-$	−2.944	2.506	0.278
EC^+	1.031	0.414	0.041
EC^-	6.276	3.862	0.148
EI^+	−2.106	1.442	0.187
EI^-	−0.667	0.264	0.039
IN^+	−0.636	0.246	0.036
IN^-	1.623	1.033	0.160
PG^+	−0.069	0.050	0.213
PG^-	−0.122	0.147	0.434
	Short-term co-integration results		
$ECPC^+$	1.7120	1.062	0.151
$ECPC^-$	−0.199	1.072	0.857
EC^+	1.616	0.687	0.051
EC^-	2.933	1.783	0.144
EI^+	−2.449	1.981	0.256
EI^-	−2.254	0.567	0.005
IN^+	−0.996	0.359	0.027
IN^-	1.010	0.952	0.323
PG^+	0.167	0.122	0.213
PG^-	−0.451	0.211	0.070

3.6. Results of Machine Learning Models

As well as the NARDL model, we applied machine learning algorithms. Initially, the dataset was distributed to training (1980 to 2012) and testing (2013 to 2016). In other words, the SVM, ANN, and LSTM models were trained with 90% of the data for training purposes and 10% of the data for testing purposes. First, the results were extracted using China's dataset to evaluate the performance of the SVM, ANN, and LSTM models with statistical metrics such as RMSE, MBE, and MAPE. The results indicate that RMSE, MBE, and MAPE provide satisfactory results for the three ML algorithms on China's dataset (Table 7). The RMSE, MAPE, and MBE values were found to be 2.099 for ANN, between 0.032 and 1.880 for SVM, and 0.006 and 1.429 for LSTM. After confirming the accuracy of the SVM, ANN, and LSTM models, the next step involved evaluating the models' performances by comparing the predicted and actual values of the output variable (CO_2e). To do so, the three algorithms were performed to predict the impact of EC, EI, ECPC, income, and population growth on CO_2e in China. Table 8 provides the predicted and actual values of CO_2e from 2013 to 2016. The results indicate that the three algorithms (SVM, ANN, and LSTM models) predicted the CO_2e close to the actual CO_2e in China, which implies that all three algorithms have an excellent ability to predict CO_2e accurately.

Table 7. Statistical metrics.

Emission Type	Country	Statistical Metrics	ANN	SVM	LSTM
CO_2e	USA	RMSE	0.020	0.021	0.021
CO_2e	USA	MAPE	1.601	1.807	1.476
CO_2e	USA	MBE	−0.011	−0.009	−0.012
CO_2e	CHINA	RMSE	0.027	0.024	0.018
CO_2e	CHINA	MAPE	2.099	1.880	1.429
CO_2e	CHINA	MBE	0.013	0.011	0.006
CO_2e	INDIA	RMSE	0.035	0.032	0.019
CO_2e	INDIA	MAPE	3.195	2.854	1.609
CO_2e	INDIA	MBE	0.030	0.027	0.015

Table 8. Actual and predicted CO_2e in China, India, and the USA.

Country	Year	Actual CO_2e	CO_2e Predicted by SVM	CO_2e Predicted by ANN	CO_2e Predicted by LSTM
China	2013	9,936,680	9,989,303	10,007,120	9,850,446
	2014	9,894,940	9,918,809	9,827,684	9,742,910
	2015	9,830,430	9,930,304	9,971,456	10,197,261
	2016	9,814,310	10,519,771	9,755,080	10,269,797
India	2013	1,966,810	1,867,127	1,903,673	1,869,096
	2014	2,136,870	2,000,476	2,103,527	1,991,179
	2015	2,150,220	2,048,106	2,094,522	2,058,733
	2016	2,183,280	2,147,102	2,115,826	2,102,843
USA	2013	5,089,500	5,725,395	5,093,302	5,124,246
	2014	5,102,580	5,839,640	5,149,849	5,158,999
	2015	4,982,790	5,805,609	5,022,575	5,101,520
	2016	4,888,640	5,802,796	4,916,199	5,092,697

Following the same procedure, the dataset was distributed to training (1980 to 2012) and testing (2013 to 2016) for India. The accuracy levels of the SVM, ANN, and LSTM models were analyzed with RMSE, MAPE, and MBE. The statistical metrics' values were found to be between −0.032 and 0.050 for SVM, 0.030 and 3.195 for ANN, and 0.015 and 1.609 for LSTM. The next step was to examine the predictive capability of the three machine learning algorithms for the case of India. The results presented in Table 8 show that SVM, ANN, and LSTM have a better-predicted capability, as the actual values and real values of the CO_2e are very close. Finally, we distributed the dataset into training (1980 to 2012) and testing (2013 to 2016) for the USA. The accuracy level of SVM, ANN, and LSTM was close to zero. The RMSE, MAPE, and MBE values lay between −0.010 and 1.601 for ANN, 0.011 and 1.807 for SVM, and −0.012 and 1.476 for LSTM. The results with the three algorithms show that the predicted CO_2e values are very close to the actual CO_2e in the USA. Overall, the three ML algorithms have an excellent capability in predicting outputs and provide satisfying results with lower values for statistical metrics. Among the three ML algorithms, the results with the ANN model can be seen more accurately in Tables 7 and 8. Table 7 presents the RMSE, MAPE, and MBE results, while Table 8 presents the actual and predicted results of CO_2e with SVM, ANN, and LSTM in China, India, and the USA. Whereas, Figure 3 provides scattered plots of China, India and USA.

3.7. Forecasting CO_2e in China (2017 to 2025)

ML algorithms, specifically ANN, provided satisfactory results for predicting the CO_2e in China, India, and the USA. Finally, this study applied the ANN model to examine the forecasted trend of CO_2e in China, India, and the USA. For more robust results, we trained algorithms for two consecutive years and then forecasted next year's CO_2e. For instance, based on 1980 and 1981, we forecasted the CO_2e for 1983. Following the same procedure, the ANN model was trained from 1980 to 2016; then, the experiment was performed to examine the CO_2e trend (forecasting) from 2017 to 2025. First, the model was performed on China's dataset. Figure 4 (China) indicates the historical and forecasted trend of CO_2e in China. Over the years, it can be seen from the figure that the CO_2e in China has remained steady; a slowdown can only be observed between 1996 and 2002. The growing trend of CO_2e from 2003 to now could be the consequence of many factors, such as the large volumes of coal, oil, petroleum, and natural gas in the energy mix of China. In recent years, China has experienced rapid growth with a change in its industrialization and urbanization. Increases in industrialization and urbanization are directly associated with the excessive consumption of energy fuels, which leads to an increase in CO_2e. China is a rapidly emerging economy, exporting steel, iron, cement, and other highly consumed energy goods around the world. These highly consumed energy products also release CO_2, causing more CO_2e in China. Since the historical trend of CO_2e in China has remained consistently upward, the forecasting trend with the ANN model from 2017 to 2025 also indicates that the CO_2e in China is a threat to the environment. Therefore, China should accelerate clean energy and promote green industrial development.

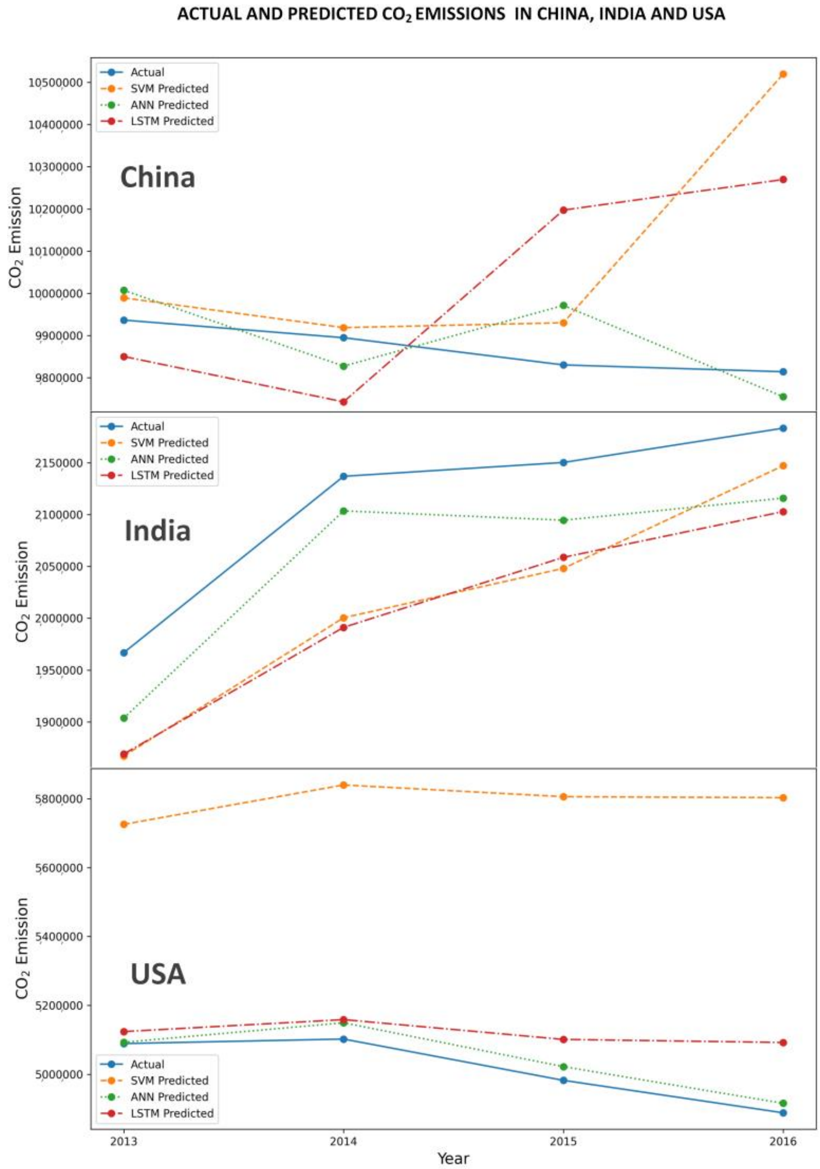

Figure 3. Scatter plot (China, India, and the USA).

3.8. Forecasting CO_2e in India (2017 to 2025)

As well as China, the ANN model was performed on India's dataset to estimate the CO_2e trend. The results presented in Figure 4 (India) show the CO_2e from 1980 to 2016, and ANN forecasted the CO_2e from 2017 to 2025. India is one of the largest countries in terms of global CO_2 emissions. Over the years, the consistently upward trend of CO_2e in India has remained a major problem in relation to environmental degradation. India's energy mix is based on fossil fuels, such as coal, oil, petroleum, and natural gas, contributing a large share of its total EC. The power sector, transportation, steel, and iron accounted for 48%, 9.9%, and 7.9% of the total CO_2e in India [37]. Consequently, industries and railways are dependent on coal, oil, and diesel in India. India is also one of the largest iron and cement producers globally. Besides its industrial and commercial sectors, India is now among the top countries for automobile sales. It is estimated that high incomes, urbanization, and power, oil, and petroleum demand will increase the CO_2e in India. The forecasted trend based on the ANN model shows a continuously increasing trend of CO_2e in India [38].

Overall, the historical trend and present situation of fossil fuels for industrial, commercial, and residential sectors exhibit that CO_2e reduction is not possible in the coming years in India. Therefore, India should strengthen its efforts to divert its energy from non-renewable to renewable energy sources and minimize other contaminated fuels that produce CO_2 and damage air quality. Our forecasted results with the ANN model on CO_2e are consistent with existing studies. For instance, Ref. [13] pointed out that CO_2e reduction is not possible at present in India. Other studies have also confirmed that CO_2e is a significant threat to environmental degradation in India [39]. Our study supports these findings and highlights the increasing trend of CO_2e in India. Regarding China, the forecasted results indicate that the CO_2e trend will remain upward in the coming years. Therefore, this evidence shows that a sharp CO_2e reduction in China and India is not possible in the coming years unless effective and urgent policies are put into place to mitigate environmental pollution. In short, both countries are required to strike a balance between their industrial, commercial, and residential sectors. Both countries should focus on the major energy-consuming industries and adopt clean and environmentally friendly policies accordingly.

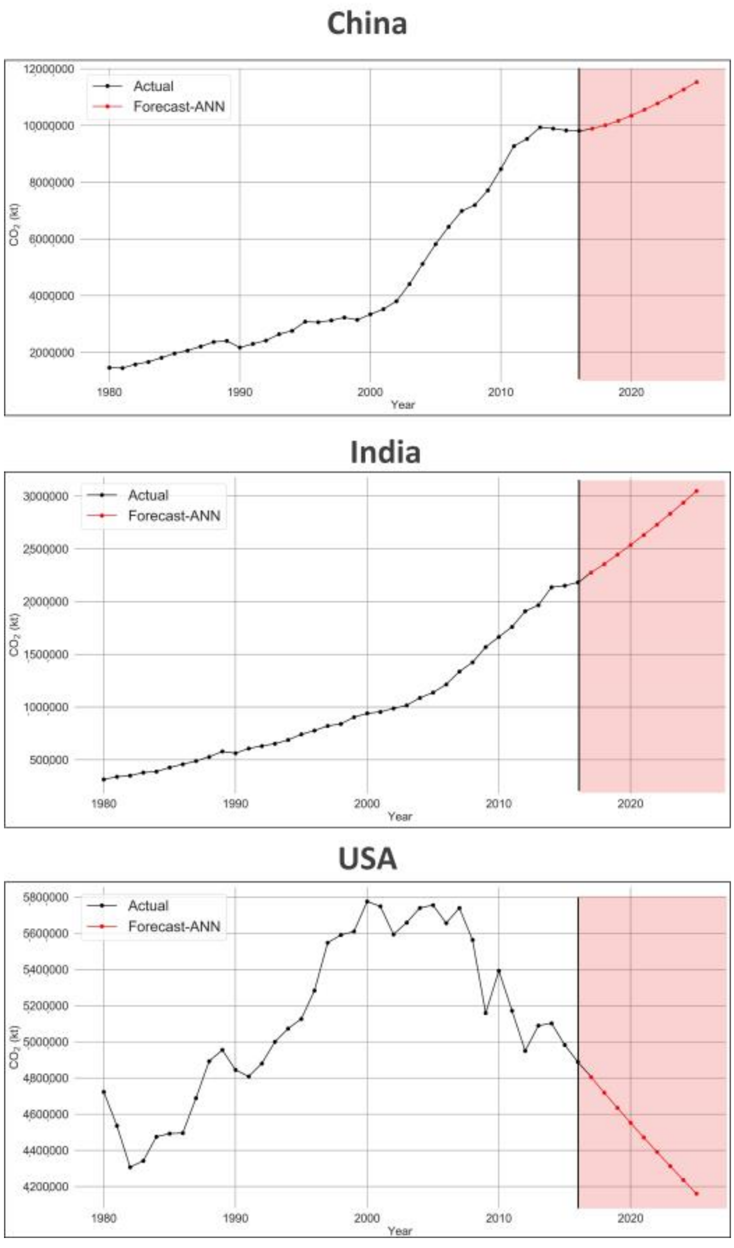

Figure 4. Yearly CO_2e emission forecasting (China, India and USA).

3.9. Forecasting CO_2e in USA (2017 to 2025)

Finally, this study forecasted the CO_2e trend in the USA. We employed the ANN model on USA's dataset and examined the CO_2e trend from 2017 to 2025. Figure 4 (USA) shows the historical and forecasted trend with the ANN model in the USA. Historically, it can be seen that, between 1990 to 2001, CO_2e remained in the upward direction in the USA; however, after 2001, CO_2e gradually dropped in USA. Petroleum is the USA's largest energy source for transportation, buildings, and industries. On the other hand, a large number of industrial (41%), residential (42%), and commercial sectors (38%) use natural gas to meet their energy demands. Recent evidence has shown that the USA has increased its clean energy sources, accounting for more than 20% of electricity from renewable energy sources. In the last decade, a slowdown in CO_2e shows that the USA has revised its energy policies. Our forecasted results with the ANN model indicate a continuous slowdown of CO_2e in the USA. These results are consistent with other studies. For instance, the findings reported in one study show a decreasing trend in CO_2e in the USA [13].

Ref. [40] investigated the empirical relation between CO_2 emissions, fossil fuel energy consumption, and economic growth. Their results based on the ARDL models confirmed that fossil fuels are the main determinant of increasing CO_2e. Ref. [41] explored the impact of non-renewable and renewable energy consumption on CO_2e emissions in China; the results revealed that an increase in non-renewable energy consumption improves CO_2e emissions significantly. Ref. [42] researched the relationship between CO_2e emissions, non-renewable energy consumption, and GDP. Based on an ARDL estimation, the findings reported that non-renewable energy consumption had a positive impact and renewable energy consumption had a negative impact on the CO_2e emissions in Turkey. On the other hand, the results of previous studies based on the LSTM model have reported that energy consumption significantly increases CO_2e emissions [43]. Research from earlier studies has also indicated that transitioning from fossil fuels to renewable energy sources offers a viable solution for long-term environmental mitigation [44]. Our findings are consistent with the previous studies and further combine the important findings based on the NARDL and machine learning models.

Overall, this study comprehensively analyzed that excessive EC affects CO_2e significantly. The findings of this study suggest that, along with increasing income, CO_2e will subsequently increase [45]. This is due to developing and emerging economies' dependency on non-renewable EC. The critical drivers of CO_2e increments are the indicators related to EC, such as the high consumption of coal, oil, petroleum, natural gas, and other contaminated fuels. Additionally, increases in ECPC and CO_2e per unit of GDP are the main reasons behind the growth of overall CO_2e. The growth of population, urbanization, and income can increase EC. With an increasing population and urbanization in China, India, and the USA, we believe the high energy demand could be the primary source of CO_2e growth. In other words, expanding ECPC, EI, and total EC with a higher volume of fossil fuels can lead to CO_2e growth.

4. Conclusions

This study aimed at investigating the influencing impact of EC, ECPC, EI, income, and population growth on CO_2e. This paper used the NARDL model to explore the association between the above-mentioned explanatory variables and CO_2e from 1980 to 2016. In the long term, the results demonstrated that ECPC significantly increases the CO_2e in China, India, and the USA. The empirical results demonstrated that EC has a long-term impact on the CO_2e in India and the USA. Furthermore, in the long term, during periods when income increased, CO_2e increased in India, but decreased in the USA. However, in the short term, when income decreased, the environmental quality improved in China and India. On the other hand, the results confirmed that population growth increases CO_2e only in India. In the case of the USA, we found that a decrease in population in the short term reduces CO_2e significantly. Regarding EI, the results revealed that a decrease in EI significantly improves the environmental quality in China and India. On the other hand, the results show that a decrease in EC in the short term and long term significantly reduces CO_2e only in China.

Lastly, the study concludes that SVM, ANN, and LSTM can predict CO_2e. The three ML models exhibited lower values of MAPE, RMSE, and MBE, indicating that SVM, ANN, and LSTM predict outcomes accurately. However, based on the overall results, the performance success of the ANN model compared to the other models was deemed to be more accurate. The forecasting trend with the ANN model from 2017 to 2025 indicates an increase in CO_2e in China and India and a decrease in CO_2e in the USA.

The results highlight the significance of considering the economic growth trajectory when formulating policies and strategies to manage and mitigate the CO_2e emissions in different countries. Adopting sustainable and eco-friendly practices in industries and businesses can facilitate a harmonious balance between economic development and environmental preservation. The contrasting responses of India and the USA to economic growth underscore the necessity of tailored environmental policies for specific national contexts. While India experienced an increase in CO_2e emissions during periods of income growth, the USA managed to decrease its emissions in similar circumstances. Identifying the underlying factors contributing to these differences could facilitate the design of targeted interventions for effective emissions control.

Our findings for the long-term and short-term effects of EC, income, and population growth on CO_2e emissions have provided a deeper understanding of the challenges and opportunities these nations face in achieving sustainable development, as they face both short-term and long-term challenges. Our findings suggest that there is a need for targeted policy interventions and initiatives to control greenhouse gas emissions. Furthermore, a crucial policy direction is the transition to renewable energy sources, reducing dependencies on fossil fuels. For instance, environmental degradation, including habitat destruction and pollution, threatens ecosystems and biodiversity worldwide.

The disparities in the prospective CO_2 emissions among India, the USA, and China are anticipated to exert differential influences on their respective environmental policies and the advancement and implementation of novel energy technologies. As China and India's economies expand, the surge in energy demand is expected to lead to escalated CO_2 emissions. Consequently, the initial environmental policies in these nations may concentrate on immediate concerns pertaining to air and water pollution, rather than imposing stringent targets for CO_2 emission reduction.

In contrast, well-developed countries like the USA are likely to possess more established environmental policies and institutions. Their focus may be on curtailing CO_2 emissions, transitioning towards low-carbon economies, and investing in renewable energy sources. This could position such developed nations at the forefront of establishing ambitious emission reduction objectives and introducing carbon-pricing mechanisms to stimulate innovation and technological advancements.

Adopting clean energy practices minimizes the environmental footprint associated with traditional energy sources, reducing habitat destruction, water contamination, and other negative impacts on ecosystems. Governments should introduce measures that incentivize the adoption of clean technologies, encourage the utilization of renewable energy sources, and facilitate the development of eco-friendly production and consumption patterns. Addressing environmental issues and promoting clean energy are of paramount importance, as they have wide-ranging benefits for society. These initiatives play a crucial role in mitigating climate change, while simultaneously fostering human well-being, economic growth, and a sustainable future. By embracing these efforts, countries dependent on fossil fuel energy consumption could pave the way for a cleaner, healthier, and more prosperous world for present and future generations.

China's and India's historical CO_2e trends highlight that both countries should accelerate clean energy fuels for sustainable development. Similarly, the USA should reduce petroleum, oil, and other fossil fuels. Contaminated fuels release greenhouse gases into the atmosphere, leading to global warming. Therefore, the governments of these countries should prioritize addressing high-power consumption sectors and industries. For instance, these three countries are the world's top iron and cement producers, and producing goods with high-carbon energy sources is undoubtedly a threat to the environment. Energy-efficient policies and technological innovation can further reduce these environmental impacts for further improvement. The empirical evidence shows that population impacts CO_2e. We must analyze whether fossil fuel consumption, coal, oil, and petroleum, etc., contribute most of the EC for residential, commercial, and industrial activities. Accordingly, there is a need to adopt cleaner energy technologies to improve economic and social development.

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