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ORIGINAL PAPER

# Analysis of energy consumption and greenhouse gas emissions trend in China, India, the USA, and Russia

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## Abstract

With the growth of industries and population, the need for energy consumption has increased, which has inevitably increased greenhouse gas emissions. Further use of fossil fuel for energy consumption exacerbates the situation making it one of the major issues for climate change. China, India, the USA, and Russia are the world's leading countries in energy consumption and emissions and are responsible for climate change. These countries account for 54% of carbon dioxide ($CO_2$) emissions in the global environment. This paper investigates the energy consumption of China, India, the USA, and Russia and its trend in greenhouse gas emissions. Using four available datasets from 1980 to 2018 for China, India, USA, and 1992 to 2018 for Russia, we employed three advanced machine learning algorithms (support vector machine, artificial neural network, and long-short term memory) and verified its predicted capability with actual greenhouse gas emissions. The obtained results were evaluated with three statistical metrics (route mean square, mean absolute percentage error, and mean bias error). The predicted results with three machine learning algorithms were very close to actual greenhouse gas emissions. Besides, we forecasted the trend of greenhouse gas emissions in these countries from 2019 to 2023. The forecasted results with the long-short term memory model confirm an increase in $CO_2$, methane, and Nitrous oxide ($N_2O$) emissions in the case of China and India; in contrast, the results indicate a slowdown of $CO_2$, methane, and $N_2O$ emissions in the USA and Russia.

**Keywords** Energy consumption · $CO_2$ emissions · Methane emissions · $N_2O$ emissions · Machine learning algorithms

## Introduction

Energy plays an important role in economic and environmental development. It is being recognized as the primary source of all the activities in our daily life to live a decent life (Jaccard et al. 2021). Its availability and accessibility to industry and households are always crucial (Bakay and Ağbulut 2021). However, the use of high carbon energy sources in developing and developed economies indicates that the consumption of fossil fuels to meet energy demands will drive greenhouse gas emissions. Fossil fuels, more specifically, coal, oil, petroleum, and natural gas, have remained high carbon contents. According to estimates, 84% of the world's energy came from burning fossil fuels in 2018 (British Petrol 2018), which directly or directly have threatened the environment, ecology, and human health (Perera 2018; Bakay and Ağbulut 2021). Consequently, World Health Organization (WHO) reports revealed, millions of people suffer from various respiratory and cardiovascular diseases, strokes, heart and lung diseases; as a result, every year, seven million people die caused by air pollution; moreover, it is one of the primary causes of premature deaths (WHO 2014).

Following the argument, most developing and developed economies are still dependent on fossil fuels for energy consumption; this dependency on inefficient energy sources contributes to the formation of greenhouse gas emissions. In other words, most Greenhouse gas emissions come from residential, commercial, transportation, and industrial sectors, where coal, petroleum, and natural gas are the primary energy source (Khan et al. 2014; Rashid et al. 2020). The International Energy Agency (IEA) reported that the global share of total final consumption of oil, natural gas, and coal accounted for 40.8%, 16.2%, and 10% in 2018 (IEA 2020),

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indicating that despite being enriched with affordable energy potential, many industrialized and emerging economies still rely on coal, oil, petroleum, and natural gas for energy consumption to power households and industries. All of these factors promote the natural greenhouse effect by releasing greenhouse gases into the atmosphere. The contaminated fuels, such as coal, oil, petroleum, etc.; emit $CO_2$, methane ($CH_4$), particulate matter, $N_2O$, and other hazardous pollutants, of which $CO_2$, $CH_4$, and $N_2O$ accounted for 76%, 16% and 6% of total greenhouse gas emissions, respectively (Bakay and Ağbulut 2021). Hence, $CO_2$, $CH_4$, and $N_2O$ have remained the most dangerous pollutants in environmental degradation. Apart from these dangerous consequences, the combustion of fossils harms social development, which reduces work effectiveness and causes a rise in health and economic expenditures (Baz et al. 2021). It is also proven that burning fossil fuels to meet energy demands has become a global issue (Karmaker et al. 2020); therefore, to achieve sustainable development goals, the nations must access and utilize efficient energy sources that are safe, reliable, and eco-friendly; for these reasons, there is an urgent need to take the path of sustainable development. Understanding the impact of these energy sources (coal, petroleum, natural gas, and renewable energy) on environmental quality is the step to reshaping energy policies. Keeping this in mind, this study was performed to bring attention to this critical topic because reducing hazardous pollutants is very important that positively impacts people, the environment, and health. Considering the aforementioned characteristics of energy mix, this study investigates the role of energy consumption in greenhouse gas emissions. Further, the study explores the trend of greenhouse gas emissions of developing and emerging economies.

China, India, the USA, and Russia are responsible for producing the most emissions (EDGAR 2021). China ranks first in coal production and consumption globally, representing 370.8 and 4319 million tons, respectively (Worldometers 2016a). Similarly, India is the world's second-largest coal producer and consumer, representing 761.66 and 966.2 million tons, respectively (Worldometers 2016b). The recent statistics show China and India generate 71% and 74% of electricity from coal resources, respectively (IEA 2019). The USA had consumed 731.1 million tons of coal as of 2016 (EIA 2016). In the case of Russia, the statistical report shows, Russia ranked sixth and fifth in coal production (423.0 Million tons) and consumption (230.3 million tons) (Worldometers 2016c; EIA 2021). The USA and Russia are also developed nations and hold the world's largest coal and natural gas reservoirs. Both countries are among the world's largest greenhouse gas emitters. Along with contaminated fuel consumption in electricity generation, today, these countries are in the race of industrial development (Khattak et al. 2020; Magazzino et al. 2021). Besides, these countries account for 41.61% of the world's population (UN 2019), which suggests these countries also need to fulfill energy demands for households and commercial activities. China, India, the USA and Russia are the world's largest emitters, and $CO_2$, methane, and $N_2O$ emissions are some of the most significant environmental challenges in these countries. In this vein, it is crucial to understand the energy consumption of these countries, its impact on greenhouse gas emissions, subsequently, greenhouse gas emissions trend in the coming years.

Since environmental pollution has been a meaningful discussion among scholars, policymakers, government personnel, and international agencies and its reduction carry equal importance for economic, social, and environmental development. With this importance, governments and policymakers have revised energy policies to reduce global warming. Some international forums on climate change (The Paris climate change agreement and Kyoto protocol) were an expression to control greenhouse gas emissions mutually. As a commitment, developing and developing countries had confirmed to lower greenhouse gas emissions to mitigate environmental pollution.

Undoubtedly, the majority of existing studies have investigated the nexus between environmental pollution, energy consumption, globalization, agriculture-livestock production, economic growth, urbanization, and trade effects (Sarkodie and Strezov 2019; Aslam et al. 2021; Rehman et al. 2021; Salari et al. 2021; Sheraz et al. 2021). However, the existing studies rarely provide a comprehensive analysis of the hazardous role of $CO_2$, methane, and $N_2O$ emissions. Besides, most studies have examined the influencing factor of energy consumption and its impact on $CO_2$ emissions; however, rare attention has been paid to the association between energy consumption and greenhouse gas emissions. Based on our understanding, none of the studies has investigated the trend of greenhouse gas emissions, particularly $CO_2$, methane, and $N_2O$ emissions, in the case of the top four countries responsible for the largest emitter in the world.

This study contributes theoretical and practical knowledge and comprehensively analyzes the greenhouse gas emissions trend. First, this study thoroughly investigates the relationship between energy consumption and greenhouse gas emissions and then forecasts greenhouse gas emissions trends in China, India, the USA, and Russia. The study analyzes the current situation of greenhouse gas emissions, provides a robust model to the countries overly dependent on fossil fuel for energy consumption, assesses its consequences on the environment, and proposes practical policy measures to address the issue. Lastly, from a methodological perspective, this study uses a novel machine learning (ML) approach with three popular algorithms to predict the influencing impact of energy consumption on greenhouse gas emissions.

This study adopts four inputs (coal, natural gas, petroleum, and renewable energy consumption) and three output variables ($CO_2$, methane, and $N_2O$ emissions) and applied available time-series data: 1980–2018 for China, India, and the USA and 1992–2018 for Russia. Three ML algorithms, such as; support vector machine (SVM), artificial neural network (ANN), and long-short term memory (LSTM), were performed and their accuracy was evaluated with route mean square error (RMSE), mean absolute percentage error (MAPE) and mean bias error (MBE). The study provides important implications to the government and policymakers in the decision-making. The results based on the ML algorithm would provide an important analysis of the greenhouse gas emission trend. The rest of the paper can be structured as follows; the next section discusses studies on the association between energy consumption and greenhouse gas emission. The third section draws a methodological part, followed by results and discussion in the fourth section. Finally, the conclusion and policy implications are presented.

## Literature review

Exploiting fossil fuels provides continuous economic growth with technological progress; however, this development simultaneously threatens climate change. By burning coal, oil, or natural gas, $CO_2$ is released into the atmosphere, and the consequences are increasing the warming of the earth's atmosphere. Consequently, methane is emitted from natural sources; these include coal mining, rice cultivation, waste, natural gas, and the burning of other fossil fuels (Crow et al. 2019). Methane is a type of hazardous gas; when emitted into the atmosphere, it severely damages air quality (Tutak and Brodny 2019). $N_2O$ is also a powerful greenhouse gas, harmful to the planet, one molecule of $N_2O$ released into the atmosphere contributes 300 times more to climate change than a single molecule of $CO_2$ (Coskun et al. 2017). The atmospheric concentration of the $N_2O$ further increased in the industrialization age; in contrast, the agriculture sector and chemical industries are also considered one of the leading causes of $N_2O$ emissions (Frutos et al. 2018).

The energy-LED theory states the cause and effect between energy consumption and environmental pollution. For instance, to understand the impact of energy consumption on carbon emissions, let us consider transportation, construction, commercial, and residential sectors, primarily based on non-renewable energy sources such as; coal, oil, petroleum, and natural gas. These non-renewable sources emit high carbon emissions and damage environmental quality. Subsequently, urbanization and industrialization have led to increased consumption of non-renewable energy sources in the last few decades. To fulfill the energy demand of these sectors, provide goods and services, and improve the living standard of people, developing and emerging economies use high carbon emission sources. Further, wastages from fossil fuel combustion have a detrimental impact on greenhouse gas emissions. In contrast, renewable energy is produced from natural sources to combat climate change. Renewable energy can decrease pollution and is one of the most reliable power sources. Renewable energy sources are the cleanest, eco-friendly, and low-cost sources (Anser et al. 2021). Given these arguments, this study views coal, petroleum, natural gas, and renewable energy as the key determinants of energy consumption and assumes its impact on $CO_2$, methane, and $N_2O$ emissions. Several studies have examined the nexus between energy consumption and environmental pollution by applying different approaches. Akhmat et al. (2014) explored the relationship between energy consumption and environmental pollutants; the results revealed that energy consumption increases $CO_2$ emissions. Khan et al. (2014) examined the long-run relationship between energy consumption and greenhouse gas emissions using data collected between 1975 and 2011. The findings confirmed a long-run relationship between energy consumption and greenhouse gas emission. Consequently, many scholars pointed out a harmful impact of energy consumption on $CO_2$ emissions (Mensah et al. 2019; Ssali et al. 2019).

Other studies, for supposing, Wang et al. (2011) attempted to examine the causal relationship between energy consumption, economic growth, and $CO_2$ emissions for China. With an annual dataset, over 1995–2007, the empirical results show a bidirectional casualty between energy consumption and renewable energy consumption; further, the results revealed that $CO_2$ emissions reduction is not possible in a long period. Govindaraju and Tang (2013), in the case of China and India, examined the nexus of coal consumption, economic growth, and $CO_2$ emissions. The results in the case of China revealed a bidirectional causal relationship between coal consumption and $CO_2$ emissions and between coal consumption and economic growth. Regarding India, the results confirmed a short-run causality and finally concluded coal consumption and $CO_2$ emissions are bi-directional. Farhani et al. (2014) examined the relationship between industrial production, coal consumption, and $CO_2$ emissions in China and India. Using a yearly dataset from 1971 to 2011 with a Granger causality test, the results show an inverted u-shaped curve in the relationship between industrial production and $CO_2$ emissions for India and U-shaped relationship for China. Shafiei and Salim (2014) investigated the determinants linked with $CO_2$ emissions. The authors used the STIRPAT model. The empirical results based on the annual dataset from 1980 to 2011 confirmed that non-renewable energy increases $CO_2$ emissions significantly. In contrast, the results supported that renewable energy plays a significant role in environmental pollution reduction. A recent study (Azam et al. 2019) investigates the empirical relationship between energy consumption, foreign direct investment (FDI), health, and the environment for China. Using a yearly data set from 1995 to 2016, the results indicate that energy consumption significantly impacts health, the environment, and foreign direct investment.

Apart from China and India, the existing studies have explored the impact of energy consumption on $CO_2$ emissions in the USA and Russia. Dogan and Turkekul (2016) examined the relationship between real output, energy consumption, trade, urbanization, financial development, and $CO_2$ emissions for the USA. The results confirmed a bidirectional causality between Gross domestic product (GDP) and $CO_2$ emissions, energy consumption and $CO_2$ emissions, urbanization, and GDP. In contrast, the study found no causality between trade openness and $CO_2$ emissions and financial development and gas emissions. Moreover, in the case of the USA, Dogan and Öztürk (2017) investigated the impact of renewable energy, non-renewable energy, and GDP on $CO_2$ emissions for a sample of 1984–2014. The results indicate that non-renewable energy consumption influences carbon emissions positively, whereas renewable energy consumption reduces environmental pollution. A more recent study in the case of the USA has been examined to know the effect of energy consumption, natural resources, and population growth on $CO_2$ emissions and ecological footprints with a dataset between 1971 and 2016. The authors concluded a bidirectional causality between $CO_2$ emissions and natural resources, ecological footprint, and natural resources, whereas the study reported that non-renewable energy degrades environmental quality (Khan et al. 2021). Rüstemoğlu and Andrés (2016) attempted to explore the determinants of $CO_2$ emissions in Russia and Brazil. The authors applied the refined Laspeyres index method. The empirical results confirmed population and economic activity accelerates $CO_2$ emissions, whereas, in the case of Russia, the results revealed energy intensity reduces $CO_2$ emissions. Kanat et al. (2021) investigated the relationship between coal, oil, gas consumption and $CO_2$ emissions. Using a dataset over 1990–2016, the empirical results confirmed that coal, oil, and gas consumption have a long-run association with $CO_2$ emissions. Moreover, the results revealed an increase in coal, oil, and gas consumption degrades environmental quality.

Further studies about greenhouse gas emissions, for instance, Sarkodie and Strezov (2019), examined the impact of FDI inflows, economic development, and energy consumption on greenhouse gas emissions for China, India, South Africa, Iran, and Indonesia. Using panel data regression with the U test estimation approach and Driscoll kraay standard error, the results reported an impact of energy consumption on greenhouse gas emissions. The study further found that FDI inflows significantly increase $CO_2$ emissions in all five countries.

### Studies on machine learning

ML methodologies are quite recent in the studies related to the environment, energy, and forecasting-related problems. ML methodologies deal with complex problems (Magazzino et al. 2021) and provide accurate results (Mitchell 2006; Başarslan and Argun 2019; Gürel et al. 2020; Mele and Magazzino 2020; Salam and Verma 2020; Ağbulut et al. 2021). Yadav and Chandel (2014) used artificial neural network (ANN) to predict solar radiation; the study concluded that ANN has more accuracy than the other model. Chiroma et al. (2015) used ANN to predict $CO_2$ emissions; the findings validated the forecasted results. More recently, Acheampong and Boateng (2019) used ANN in modeling $CO_2$ intensity for the countries China, India, Australia, Brazil, and the USA. The authors used nine inputs to predict the growth of $CO_2$ emissions. The results confirmed the highest accuracy in the training and prediction success. Besides ANN, ML algorithms such as SVM (Bakay and Ağbulut 2021) and LSTM are popular in predicting and forecasting (Zheng et al. 2019). LSTM has a wide range of implementation predicting the results with time-series data (Cortez et al. 2018). The study conducted by Huang et al. (2019) used sixteen inputs to predict $CO_2$ emissions. Using backpropagation neural network, Gaussian process regression, and LSTM, the results revealed that LSTM has more capability of predicting $CO_2$ emissions accurately.

Overall, the existing literature demonstrates that energy consumption with fossil fuels is a threat to the environment and health. Many studies have examined the empirical relationship of energy consumption on environmental pollution and economic development with different approaches. Most of the existing studies have investigated either the impact of energy consumption on economic development, health, and environmental pollution or considers only $CO_2$ emissions as a determinant of greenhouse gas emissions. In contrast, very few studies evaluate the other kinds of greenhouse gas emissions. Besides, the existing literature lacks comprehensive findings on energy consumption in $CO_2$, methane, and $N_2O$ emissions. This study invites necessary attention towards the top four countries (China, India, USA, and Russia) responsible for the most significant emitter and other economies overly dependent on fossils fuels for energy consumption.

## Materials and methods

### Data sources

This study used four influencing factors: coal, petroleum-liquids, natural gas, and renewable energy consumption as input variables for $CO_2$, methane, and $N_2O$ emissions as output variables. Four available datasets: 1980–2018 for China, India, and the USA, and 1992–2018 for Russia, were applied to analyze the results. Data on coal, petroleum-liquids, natural gas, and renewable energy consumption is expressed in quad Btu and were downloaded from U.S Energy Information (EIA 2018). $CO_2$, methane, and $N_2O$ emissions are expressed in kt, kt of $CO_2$ equivalent, and thousand metric tons of $CO_2$ equivalent, respectively. The $CO_2$, methane, and $N_2O$ emissions data were downloaded from the World Bank Indicators (Worldbank 2018).

## Methodology

ML brings the promise of deriving meaning from all of the data types collected worldwide, such as texts, spreadsheets, pictures, etc. ML uses fewer assumptions than traditional statistical and econometric techniques; these statistical techniques are widely used to predict the relationship between variables. ML algorithms have a strong predictive power as the algorithms are trained to find patterns. ML algorithms learn the data automatically based on previous records, which is inconsistent with certain traditional methods of analyzing data. The predicted model can be further used to predict previously unknown data and solve problems. As more data are gathered, the model can provide better results. In other words, ML methods can solve the problem with accuracy, consistency, and an unbiased manner (Elmaz et al. 2020). The algorithm relied on "learning" the new data and gradually improved. ML algorithms also use a technique known as "self-learning," where relevant information is accessed through data analysis without requiring explicit programming. ML methods provide robust results, limit the risks of errors, and can be easily used for classification, regression, and prediction-related problems (Bibault et al. 2016; Rustam et al. 2020).

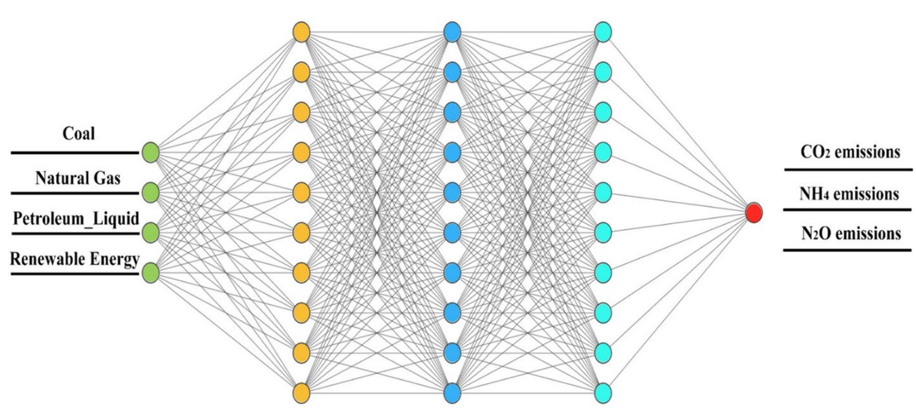
This study adopts structured learning, also called deep learning, a class of ML algorithms. Deep learning uses a multi-layer approach to extract the features from the available data. The deep learning model can learn the pattern of a sequence and predict the desired output. SVM, ANN, and LSTM are popular in predicting outcomes and represent a widely accepted deep learning technique to solve problems (Bibault et al. 2016; Huang et al. 2019). Moreover, these three algorithms are popular in prediction and forecasting related problems. Since this study examines the impact of energy consumption on greenhouse gas emissions using time series data and further forecasts the trend of greenhouse gas emissions, ML algorithms can be a suitable technique for accurately predicting outcomes.

## SVM, ANN and LSTM model

SVM is a kind of supervised ML algorithm commonly used in many areas such as face detection, classification of images, regressions (Aslam et al. 2020; Quan et al. 2020; Wei et al. 2020). SVM is also one of the popular algorithms, has been used in recent studies for the problems related to prediction (Tang et al. 2019). SVM relies on computational and statistical learning and works with kernel function, epsilon, and C value, which are the three basic parameters (Bakay and Ağbulut 2021). Many studies support that SVM has a high generalization capability (Torabi et al. 2018). Moreover, this algorithm does not require additional layers (Bakay and Ağbulut 2021). ANN relies on the mathematical model, which functions like neurons (Almansour et al. 2019). ANN has many applications in the stock market predictions, time series related problems, and other real-life issues (Kamuda et al. 2017). ANN works through learning and has an ability to remember and generalize once properly trained the algorithm. ANN is commonly used in classifications, regressions, noise reduction, and prediction (Prasad and Edward 2017; Bakay and Ağbulut 2021). Figure 1 defines the structure of the ANN architecture.

Finally, LSTM is popular in predicting output and widely accepted to solve time series problems. LSTM consists of input, hidden, and output layers. Each of the multiple nodes is input layers representing the individual features from the dataset that we pass to the model. Each of these inputs is connected with the next layer, the next layer representing the hidden layer.

**Fig. 1** ANN structure



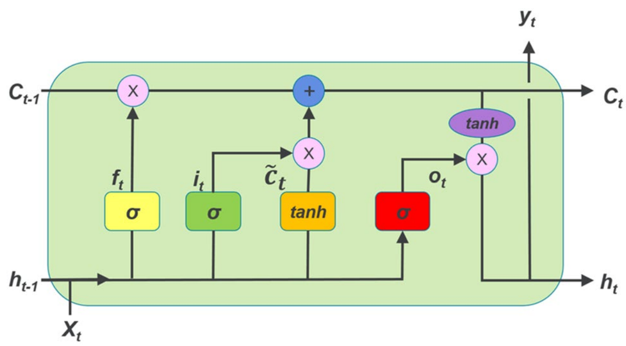



**Fig. 2** Architectural structure of LSTM

In other words, the hidden layer works between the input layers and output layer. Figure 2 defines the LSTM structure. First, three gates, namely, the input gate, forget gate, and output gate, which are represented with ($i_t$), ($f_t$), and ($O_t$), respectively, can be computed through Eqs. (1)–(3). Each of the gates and each of the cell's gates has a corresponding weight; for example, ($i_t$), ($f_t$), and ($O_t$) have their own weights. ($f_t$) decides which information has to be retained or dropped; ($i_t$) decides which information should be saved to the cell or dropped, and ($O_t$) indicates which information should be sent to the next hidden state. Equations (1) and (4) show that ($i_t$) selectively records new information in the cell state ($c_t$). However, in Eq. (5), ($f_t$) selectively discards information from the previous cell state. $c_{t-1}$ and $ct$ represent the cell state at times $t-1$ and $t$, respectively. ($g_t$) includes information on the cell state. Finally, ($O_t$) generates information for the next cell, as presented in Eq. (6). The following equations are used to describe the driving process of the LSTM approach and Fig. (2) defines the LSTM structure.

$$i_t = \sigma(W_i x_t + R_i h_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma(W_f x_t + R_f h_{t-1} + b_f) \tag{2}$$

$$o_t = \sigma(W_o x_t + R_o h_{t-1} + b_o) \tag{3}$$

$$g_t = tanh(W_g x_t + R_g h_{t-1} + b_g) \tag{4}$$

$$c_t = f_t * c_{t-1} + g_t * i_t) \tag{5}$$

$$h_t = o_t * \tanh(c_t) \tag{6}$$

where $\sigma$ = Sigmoid function, $W$ = input weight, $R$ = Recurrent weight, $h_{t-1}$ = old state, $x_t$ = input, $b$ = bias.

## Results and discussion

The dataset was distributed into training: 1980–2015 for China, India, the USA, 1992–2015 for Russia, and 2019–2023 for testing purposes. Initially, the algorithms were performed to examine the accuracy of SVM, ANN, and LSTM models. The results presented in Table 1 show

**Table 1** Results of statistical metrics

| Emission type | Statistical metrics | LSTM | ANN | SVM |
|---|---|---|---|---|
| *Results of statistical metrics (China)* | | | | |
| $CO_2$ | RMSE | 0.023 | 0.028 | 0.021 |
| $CO_2$ | MAPE | 1.992 | 2.272 | 1.662 |
| $CO_2$ | MBE | – 0.019 | 0.0217 | 0.015 |
| Methane | RMSE | 0.007 | 0.016 | 0.041 |
| Methane | MAPE | 0.535 | 1.371 | 3.313 |
| Methane | MBE | 0.003 | 0.011 | 0.031 |
| $N_2O$ | RMSE | 0.010 | 0.035 | 0.027 |
| $N_2O$ | MAPE | 0.963 | 3.041 | 2.394 |
| $N_2O$ | MBE | – 0.004 | 0.020 | 0.013 |
| *Results of statistical metrics (India)* | | | | |
| $CO_2$ | RMSE | 0.060 | 0.008 | 0.024 |
| $CO_2$ | MAPE | 4.175 | 0.705 | 2.122 |
| $CO_2$ | MBE | – 0.047 | – 0.006 | – 0.019 |
| Methane | RMSE | 0.007 | 0.004 | 0.000 |
| Methane | MAPE | 0.616 | 0.342 | 0.050 |
| Methane | MBE | – 0.006 | – 0.003 | – 0.000 |
| $N_2O$ | RMSE | 0.020 | 0.0146 | 0.004 |
| $N_2O$ | MAPE | 1.667 | 1.211 | 0.271 |
| $N_2O$ | MBE | – 0.016 | – 0.011 | 0.002 |
| *Results of statistical metrics (USA)* | | | | |
| $CO_2$ | RMSE | 0.021 | 0.0205 | 0.013 |
| $CO_2$ | MAPE | 1.743 | 1.642 | 0.993 |
| $CO_2$ | MBE | – 0.016 | – 0.015 | – 0.009 |
| Methane | RMSE | 0.013 | 0.013 | 0.010 |
| Methane | MAPE | 1.121 | 1.069 | 0.777 |
| Methane | MBE | – 0.011 | – 0.010 | – 0.004 |
| $N_2O$ | RMSE | 0.003 | 0.003 | 0.035 |
| $N_2O$ | MAPE | 0.252 | 0.344 | 2.508 |
| $N_2O$ | MBE | – 0.002 | – 0.002 | 0.023 |
| *Results of statistical metrics (Russia)* | | | | |
| $CO_2$ | RMSE | 0.032 | 0.031 | 0.0176 |
| $CO_2$ | MAPE | 2.400 | 2.410 | 1.496 |
| $CO_2$ | MBE | – 0.025 | – 0.025 | – 0.014 |
| Methane | RMSE | 0.002 | 0.002 | 0.030 |
| Methane | MAPE | 0.230 | 0.279 | 2.428 |
| Methane | MBE | – 0.001 | – 0.000 | 0.0217 |
| $N_2O$ | RMSE | 0.005 | 0.004 | 0.009 |
| $N_2O$ | MAPE | 0.354 | 0.325 | 0.641 |
| $N_2O$ | MBE | – 0.003 | – 0.002 | 0.005 |

the calculated values of three different statistical metrics: RMSE, MAPE, and MBE. The statistical metrics are used to check how the forecasting performs accurately. RMSE, MAPE, and MBE are widely used accuracy measures. MBE is a commonly applied statistical metric that provides knowledge about the performance of a model. It is recommended that the MBE values close to zero are better, and the lowest values further confirm that algorithms can predict output exactly (Fan et al. 2019). Whereas, MAPE gives information about how well a metric accurately predicts the results, as a percentage, MAPE represents the size of error (Zang et al. 2020). It is also recommended that the values close to zero are preferable, which defines the forecasting models are accurately predicted. RMSE is the standard deviation of the residuals, and it gives a number that determines the accuracy and performance of a model; also, RMSE indicates a difference between predicted and actual data (Zang et al. 2020). First, the algorithms were performed on China's dataset. All three statistical metrics confirm the satisfactory results of the three ML algorithms for China. The RMSE, MAPE, and MBE values range between 3.31 and 0.01, indicating the goodness of the three algorithms. Based on these results, although three models depict the performance success of three algorithms, however, compared to ANN and SVM, LSTM provides better results with values close to 0. The next step was performed to test the actual and predicted values of $CO_2$, methane, and $N_2O$ emissions with three algorithms for China. Table 2 provides three years of $CO_2$, methane, and $N_2O$ emissions from 2016 to 2018 for China. The results with three algorithms indicate that predicted $CO_2$, methane, and $N_2O$ emissions are very close to the actual $CO_2$, methane, and $N_2O$ emissions. This means that all three algorithms have excellent capability in predicting output accurately.

Similarly, the dataset was distributed into training (1980–2015) and testing (2016–2018) set for India. Then, the statistics metrics of RMSE, MAPE, and MBE have analyzed the accuracy level of ANN, SVM, and LSTM algorithms for India. All three algorithms show better results on the data applied for India with lower RMSE, MAPE, and MBE values, and in most cases, the values were found close to zero. The values of statistical metrics ranged between 4.17 and − 0.01 for ANN, SVM, and LSTM models. After confirming the accuracy level of RMSE, MAPE, and MBE, the three ML algorithms predicted $CO_2$, methane, $N_2O$ emissions for India. The results presented in Table 2 show that SVM, ANN, and LSTM have better-predicted capability, as predicted values are close to actual values. However, in predicting $N_2O$ emissions, the results indicate that ANN partially failed to forecast the well-matched results.

Apart from China and India, we applied the same procedure for the USA and Russia. The dataset was distributed into training (1980–2015) and testing (2016–2018) set for the USA. The accuracy level of three ML algorithms was confirmed with lower RMSE, MAPE, and MBE values, on the USA's data. Overall the results provide satisfactory results; the values of RMSE, MAPE, and MBE lie between 2.50 and − 0.01 for the USA. It was observed that ANN and LSTM provide more accurate results than SVM in statistical metrics in the USA. The results with three algorithms indicate that predicted $CO_2$, methane, and $N_2O$ emissions are very close to the actual $CO_2$, methane, and $N_2O$ emissions in the USA. Finally, the data were divided into training (1992–2015) and testing (2016–2018) set for Russia. The results presented in Table 1 indicate that the values of all the three statistical metrics ranged between 2.428 and − 0.000, indicating the ANN, SVM, and LSTM algorithms provide very satisfactory results for Russia. Consequently, in forecasting $CO_2$, methane, and $N_2O$ emissions, the results with three algorithms were found very close to the actual $CO_2$, methane, and $N_2O$ emissions. Table 1 presents the results of statistical metrics, and Table 2 presents the actual greenhouse gas emissions and results predicted with three algorithms.

### *Forecasting $CO_2$, methane, and $N_2O$ emissions in China*

LSTM is a very useful technique in forecasting time series-related problems (Huang et al. 2019). As confirmed in the above results, the ML algorithm provides very satisfactory results in predicting greenhouse gas emissions; then, the next step was performed to analyze the $CO_2$, methane, and $N_2O$ emissions trend from 2019 to 2023. To do so, the dataset was divided into three consecutive years to forecast the fourth year's emissions. Starting from 1980, 1981, and 1982, the algorithms were trained on datasets to predict $CO_2$, methane, and $N_2O$ emissions of 1983 for each country (China, India, and the USA); then, we took three more years, 1981, 1982, and 1983, and trained the LSTM model accordingly to forecast the fourth year's (1984) emissions. In this way, from 1980 to 2018, three consecutive years were employed to predict more accurate results.

Following the above procedure, the algorithm forecast China's $CO_2$, methane, and $N_2O$ emissions from 2019 to 2023 separately. As shown in Fig. 3, the historical trend of $CO_2$ emission in China shows a continuous increase in $CO_2$ emission from 1980 to 2018. The major contribution of China's energy sector is based on coal consumption. In 1980, China used 13.81 quad Btu of coal for energy consumption, and subsequently, this rate was increased in the following years. The current statistics show; China consumed 90.36 quad Btu in 2018 in total energy consumption. Furthermore, based on 2019 statistics, China consumed around 64% of coal to meet energy demand (IEA 2020), accounted 52% of global coal consumption

**Table 2** Actual and predicted emissions with ANN, SVM, and LSTM algorithms

| Year | Actual $CO_2$ emissions | ANN ($CO_2$ emissions) | Actual Methane emissions | ANN (Methane emissions) | Actual $N_2O$ emissions | ANN ($N_2O$ emissions) |
|---|---|---|---|---|---|---|
| *Actual and predicted emissions with ANN, SVM, and LSTM algorithms (China)* | | | | | | |
| 2016 | 9,814,310 | 9,591,235 | 1,242,150 | 1,096,398 | 546,990 | 536,167 |
| 2017 | 10,017,770 | 10,054,125 | 1,239,130 | 1,089,806 | 542,100 | 550,989 |
| 2018 | 10,313,460 | 10,575,460 | 1,238,630 | 1,094,988 | 538,790 | 567,638 |
| Year | Actual $CO_2$ emissions | SVM ($CO_2$ emissions) | Actual Methane emissions | SVM (Methane emissions) | Actual $N_2O$ emissions | SVM ($N_2O$ emissions) |
| *Actual and predicted emissions with ANN, SVM, and LSTM algorithms (China)* | | | | | | |
| 2016 | 9,814,310 | 8,983,159 | 1,242,150 | 1,159,729 | 546,990 | 545,030 |
| 2017 | 10,017,770 | 9,371,791 | 1,239,130 | 1,196,074 | 542,100 | 556,983 |
| 2018 | 10,313,460 | 9,788,371 | 1,238,630 | 1,239,193 | 538,790 | 569,647 |
| Year | Actual $CO_2$ emissions | LSTM ($CO_2$ emissions) | Actual Methane emissions | LSTM (Methane emissions) | Actual $N_2O$ emissions | LSTM ($N_2O$ emissions) |
| *Actual and predicted emissions with ANN, SVM, and LSTM algorithms (China)* | | | | | | |
| 2016 | 9,814,310 | 8,983,159 | 1,242,150 | 1,159,729 | 546,990 | 545,030 |
| 2017 | 10,017,770 | 9,371,791 | 1,239,130 | 1,196,074 | 542,100 | 556,983 |
| 2018 | 10,313,460 | 9,788,371 | 1,238,630 | 1,239,193 | 538,790 | 569,647 |
| Year | Actual $CO_2$ emissions | ANN ($CO_2$ emissions) | Actual Methane emissions | ANN (Methane emissions) | Actual $N_2O$ emissions | ANN ($N_2O$ emissions) |
| *Actual and predicted emissions with ANN, SVM, and LSTM algorithms (India)* | | | | | | |
| 2016 | 2,183,280 | 2,222,872.8 | 657,690 | 585,740 | 245,150 | 191,282 |
| 2017 | 2,301,440 | 2,316,487.8 | 661,610 | 587,457 | 248,300 | 192,369 |
| 2018 | 2,434,520 | 2,438,754 | 666,510 | 589,668 | 253,790 | 193,800 |
| Year | Actual $CO_2$ emissions | SVM ($CO_2$ emissions) | Actual Methane emissions | SVM (Methane emissions) | Actual $N_2O$ emissions | SVM ($N_2O$ emissions) |
| *Actual and predicted emissions with ANN, SVM, and LSTM algorithms (India)* | | | | | | |
| 2016 | 2,183,280 | 1,727,864 | 657,690 | 671,921 | 245,150 | 255,964 |
| 2017 | 2,301,440 | 1,738,345 | 661,610 | 676,531 | 248,300 | 261,081 |
| 2018 | 2,434,520 | 1,747,138 | 666,510 | 680,723 | 253,790 | 267,007 |
| Year | Actual $CO_2$ emissions | LSTM ($CO_2$ emissions) | Actual Methane emissions | LSTM (Methane emissions) | Actual $N_2O$ emissions | LSTM ($N_2O$ emissions) |
| *Actual and predicted emissions with ANN, SVM, and LSTM algorithms (India)* | | | | | | |
| 2016 | 2,183,280 | 1,788,250 | 657,690 | 568,833 | 245,150 | 243,040 |
| 2017 | 2,301,440 | 1,846,982 | 661,610 | 569,251 | 248,300 | 243,662 |
| 2018 | 2,434,520 | 1,913,011 | 666,510 | 569,696 | 253,790 | 244,218 |
| Year | Actual $CO_2$ emissions | ANN ($CO_2$ emissions) | Actual Methane emissions | ANN (Methane emissions) | Actual $N_2O$ emissions | ANN ($N_2O$ emissions) |
| *Actual and predicted emissions with ANN, SVM, and LSTM algorithms (USA)* | | | | | | |
| 2016 | 4,888,640 | 5,157,522 | 609,200 | 666,585 | 248,510 | 290,946 |
| 2017 | 4,813,720 | 5,159,923 | 614,500 | 666,883 | 249,290 | 291,142 |
| 2018 | 4,981,300 | 5,170,007 | 622,590 | 667,737 | 250,060 | 290,654 |
| Year | Actual $CO_2$ emissions | SVM ($CO_2$ emissions) | Actual Methane emissions | SVM (Methane emissions) | Actual $N_2O$ emissions | SVM ($N_2O$ emissions) |
| *Actual and predicted emissions with ANN, SVM, and LSTM algorithms (USA)* | | | | | | |
| 2016 | 4,888,640 | 5,214,983 | 609,200 | 588,485 | 248,510 | 248,436 |

**Table 2** (continued)

| Year | Actual $CO_2$ emissions | SVM ($CO_2$ emissions) | Actual Methane emissions | SVM (Methane emissions) | Actual $N_2O$ emissions | SVM ($N_2O$ emissions) |
|---|---|---|---|---|---|---|
| 2017 | 4,813,720 | 5,211,591 | 614,500 | 580,014 | 249,290 | 252,946 |
| 2018 | 4,981,300 | 5,274,846 | 622,590 | 590,297 | 250,060 | 237,655 |
| Year | Actual $CO_2$ emissions | LSTM ($CO_2$ emissions) | Actual Methane emissions | LSTM (Methane emissions) | Actual $N_2O$ emissions | LSTM ($N_2O$ emissions) |
| *Actual and predicted emissions with ANN, SVM, and LSTM algorithms (USA)* | | | | | | |
| 2016 | 4,888,640 | 5,144,730 | 609,200 | 666,051 | 248,510 | 291,620 |
| 2017 | 4,813,720 | 5,146,774 | 614,500 | 666,331 | 249,290 | 291,724 |
| 2018 | 4,981,300 | 5,149,460 | 622,590 | 666,686 | 250,060 | 291,926 |
| Year | Actual $CO_2$ emissions | ANN ($CO_2$ emissions) | Actual Methane emissions | ANN (Methane emissions) | Actual $N_2O$ emissions | ANN ($N_2O$ emissions) |
| *Actual and predicted emissions with ANN, SVM, and LSTM algorithms (Russia)* | | | | | | |
| 2016 | 1,530,900 | 1,595,653 | 852,550 | 734,073 | 58,060 | 57,557 |
| 2017 | 1,557,190 | 1,597,512 | 850,170 | 735,610 | 58,660 | 57,638 |
| 2018 | 1,607,550 | 1,599,010 | 849,570 | 736,744 | 58,610 | 57,697 |
| Year | Actual $CO_2$ emissions | SVM ($CO_2$ emissions) | Actual Methane emissions | SVM (Methane emissions) | Actual $N_2O$ emissions | SVM ($N_2O$ emissions) |
| *Actual and predicted emissions with ANN, SVM, and LSTM algorithms (Russia)* | | | | | | |
| 2016 | 1,530,900 | 1,565,391 | 852,550 | 842,715 | 58,060 | 52,755 |
| 2017 | 1,557,190 | 1,588,991 | 850,170 | 866,119 | 58,660 | 54,041 |
| 2018 | 1,607,550 | 1,606,033 | 849,570 | 886,086 | 58,610 | 54,169 |
| Year | Actual $CO_2$ emissions | LSTM ($CO_2$ emissions) | Actual Methane emissions | LSTM (Methane emissions) | Actual $N_2O$ emissions | LSTM ($N_2O$ emissions) |
| *Actual and predicted emissions with ANN, SVM, and LSTM algorithms (Russia)* | | | | | | |
| 2016 | 1,530,900 | 1,594,296 | 852,550 | 731,486 | 58,060 | 57,490 |
| 2017 | 1,557,190 | 1,595,176 | 850,170 | 731,929 | 58,660 | 57,521 |
| 2018 | 1,607,550 | 1,596,038 | 849,570 | 732,355 | 58,610 | 57,552 |

in 2019 as reported in the yearbook (Enerdata 2019). Consequently, methane emissions in China increased linearly over the years. Figure 3 depicts a trend of methane emissions in China from 1980 to 2018, and LSTM predicted methane emissions from 2019 to 2023. Only a slowdown of methane emission was observed during the 1990s period. Methane emission of China in 1980 was equal to 53.86 qua Btu, with a continuous increase, it reached up to 144.16 quad Btu in 2018. China ranks third in natural gas consumption and consumes 6.4% of the world's total consumption, with 5929 cubic feet of natural gas per capita (Worldometers 2017). The high volume of coal and natural gas consumption in China is to meet energy demand in the country. Similarly, the algorithm was performed to analyze the $N_2O$ emissions trend from 2019 to 2023 in China. Figure 3 shows the historical and forecasted trend of $N_2O$ emissions in China. As it can be seen in Fig. 3, $N_2O$ emissions show a consistently increasing trend. In 1980, $N_2O$ emissions were recorded with a value of 237,185 (thousand metric tons of $CO_2$ equivalent), which reached 538,790 (thousand metric tons of $CO_2$ equivalent) in 2018 (Worldbank 2018).

The historical trend of China's $CO_2$, methane, and $N_2O$ emissions remained consistently upward. The forecasted values with the LSTM model also show an increasing trend of greenhouse gas emissions in China. According to the thirteenth five-year plan, $CO_2$ emissions as a percentage of GDP were 0.38, which indicates a significant drop of 30% than a target drop of 18% (Huang et al. 2019). Furthermore, according to Global Energy Statistical Yearbook 2021, china has covered 28% of the energy with renewable energy. These policies are in action to mitigate environmental pollutants. However, the forecasted greenhouse gas emissions trend indicates the increasing rate of fossils fuel significantly influences $CO_2$, methane, and $N_2O$ emissions in China. In the current stage, China must consider $CO_2$, methane and $N_2O$

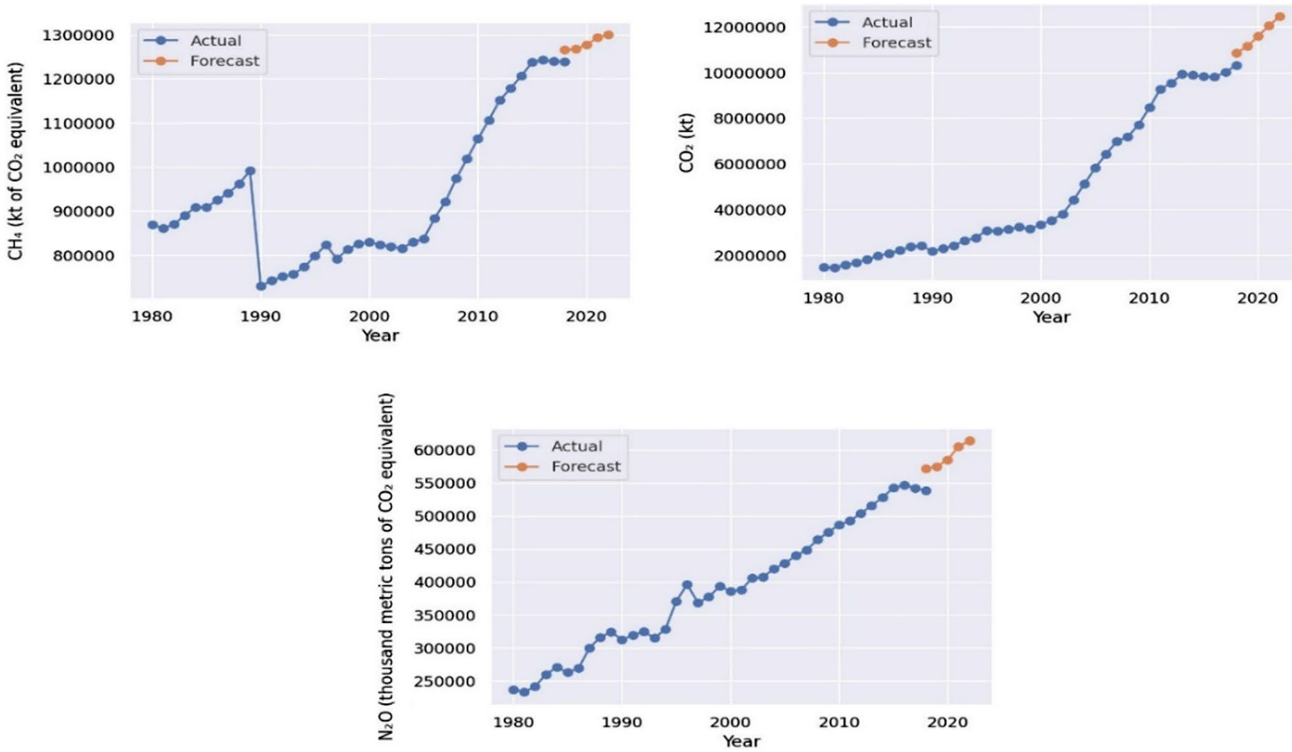



**Fig. 3** Yearly $CO_2$, methane and $N_2O$ emissions trend in China

emission mitigations in the following decades based on its energy consumption.

### *Forecasting $CO_2$, methane, and $N_2O$ emissions in India*

Next, the algorithm was performed to examine India's greenhouse gas emissions trend (2019–2023). The results presented in Fig. 4 show $CO_2$, methane, and $N_2O$ emissions in India from 1980 to 2018, and LSTM forecasted $CO_2$, methane, and $N_2O$ emissions from 2019 to 2023. India ranked second-largest country globally in $CO_2$ emission. A continuous trend of $CO_2$ emission from 1980 shows that India's energy consumption depends mainly on fossil fuel consumption. The historical record shows that India used 1.82 quad BTU of coal in 1980, which increased up to 16.39 quad BTU in 2018. India's electricity sector, mainly dependent on coal consumption, accounted for 75.31% of electricity generation from coal (Worldbank 2018). Consequently, as shown in Fig. 4, the historical trend concerning methane emissions indicates an increasing trend year by year in India. In 1980, India's methane emission was recorded with a value of 444,528 (kt of $CO_2$ equivalent), which increased up to 666,510 (kt of $CO_2$ equivalent) in 2018. An increase in natural gas consumption in India is associated with the production of energy-consumed goods, which implies that the industrial sector will contribute to a growing demand for natural gas in India (EIA 2019). Furthermore, due to the high energy demand, goods, iron, and steel, would surpass China's natural gas consumption in India after 2040 (EIA 2019). As shown in Fig. 4, $N_2O$ emissions indicate an increasing trend over the years. Only a slowdown can be seen in 1990 and 2000. India's $N_2O$ emission was recorded with a value of 114,802 (thousand metric tons of $CO_2$ equivalent) in 1980, which gradually increased up to 253,790 (thousand metric tons of $CO_2$ equivalent) in 2018. Rice and wheat production is the major source of $N_2O$ emissions in India, which is about 17 million tons (Tewatia and Chanda 2017); of this, 70% is used in cereal production (Bijay and Singh 2017). It is also estimated that to meet increasing population's demand in India, the consumption of N-fertilizer is expected to grow by 24 million tons in 2030 (Tewatia and Chanda 2017).

Figure 4 shows India's historical and forecasted $CO_2$, methane, and $N_2O$ emissions trends. India ranks as one of the responsible countries globally in terms of $CO_2$ emissions. The main sources of $CO_2$ emission in India are fossil fuel consumption (MK 2020). The excessive consumption of fossil fuels for electricity generation and to fulfill energy demand in industrial activities is alarming. Overall, the results in the case of China and India are similar, as the forecasted trend of three pollutants (from 2019 to 2023) shows an upward direction. Therefore, both countries need to divert their energy consumption from non-renewable to renewable energy consumption. Besides, both countries are

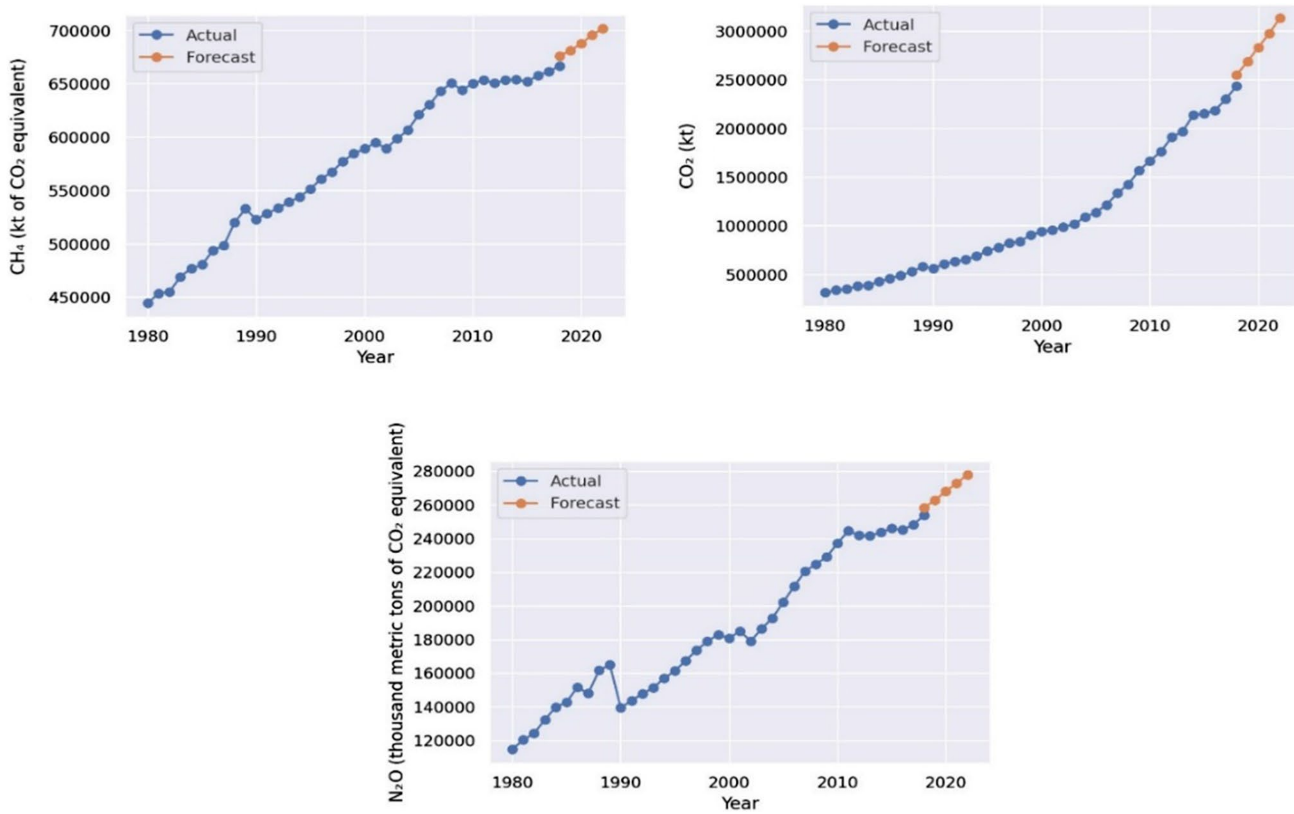



**Fig. 4** Yearly $CO_2$, methane and $N_2O$ emissions trend in India

the most populated globally; therefore, more energy demand is expected. In this regard, it is urgent to speed clean energy policies to benefit environmental, social, and economic development.

## Forecasting $CO_2$, methane, and $N_2O$ emissions in the USA

Next, the LSTM model was performed to examine the greenhouse gas emissions trend in the USA. The results presented in Fig. 5 show a historical $CO_2$, methane, and $N_2O$ emissions trend from 1980 to 2018 and LSTM predicted trend from 2019 to 2023. The results indicate that during the 90 s, $CO_2$ emissions gradually increased in the USA. In 1991, the $CO_2$ emissions were recorded with a value of 4,808,090 (kt of $CO_2$ equivalent), which increased consequently up to 2000 (year). However, after 2001, the $CO_2$ emissions trend were slowdown and reached up to 4,981,300 (kt of $CO_2$ equivalent). Regarding coal consumption, the historical data shows, USA consumed 15.42 quad BTU in 1980 and gradually decreased coal consumption up to 13.52 quad Btu in 2018. In 1980, USA's methane emissions were recorded with a value of 607,555 (thousand metric tons of $CO_2$ equivalent). However, during ten years' period, the USA's methane emission gradually increased from 607,640 (thousand metric tons of $CO_2$ equivalent) in 1984 to 758,520 (thousand metric tons of $CO_2$ equivalent) in 1994. As seen in Fig. 5, after 1995, the USA's methane emission declined gradually and reached up to 602,590 (thousand metric tons of $CO_2$ equivalent) in 2018. However, the historical trend shows that the USA consumed 20.23 quad Btu of natural gas in 1980 and gradually increased its consumption to 31.15 quad Btu in 2018. Similarly, petroleum consumption was recorded with a value of 34.15 quad Btu in 1980, and it reached a level of 38.35 quad BTU in 2018. This implies that the USA shifted energy consumption sources from coal to petroleum, natural gas, and other sources. Regarding $N_2O$ emissions, a value of 376,718 (thousand metric tons of $CO_2$ equivalent) was recorded in 1980, which gradually decreased to 250,060 (thousand metric tons of $CO_2$ equivalent) in 2018.

The USA uses different energy consumption sources such as coal, natural gas, petroleum, nuclear, and petroleum. Among primary energy consumption sources, the USA relies 35% of energy consumption on petroleum, 34% on natural gas, 12% on renewable energy, 10% on coal, and 9% on other energy sources (EIA 2020). With 33% and 90%, the Industrial and transportation sector depends on petroleum consumption, respectively. According to the US energy information administration (EIA 2020), 41%, 42%, and 38% of industrial, residential, and commercial activities run

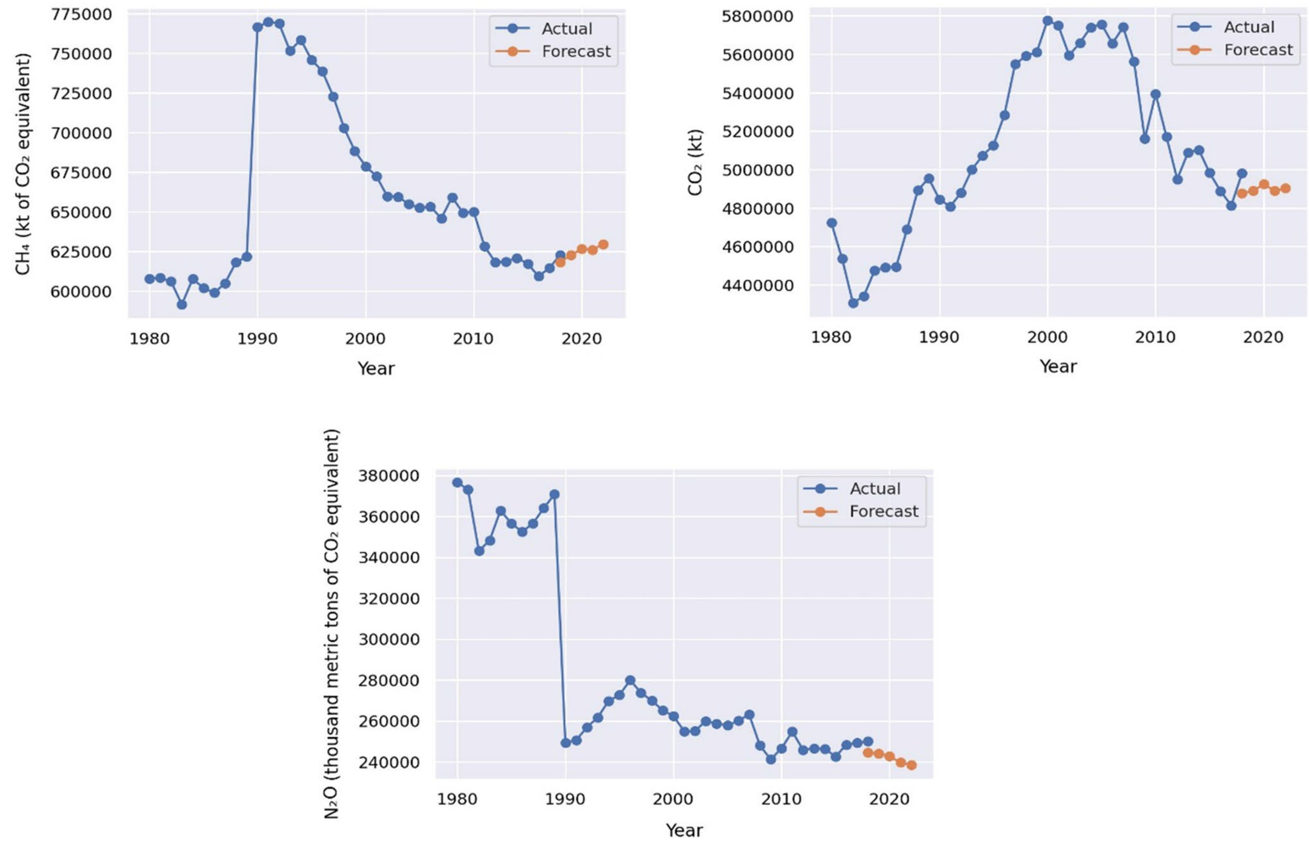



**Fig. 5** Yearly $CO_2$, methane and $N_2O$ emissions trend in USA

through natural gas consumption. This evidence shows that the USA's primary energy consumption depends on petroleum and natural gas consumption to meet energy demand.

Although, in recent years, $CO_2$, methane, and $N_2O$ emissions were seen with a declining trend (see Fig. 5), however, still a high volume of fossils fuel consumption is being used for energy consumption in the USA. Compared to China and India, the results in the case of the USA indicate a continuous slowdown of coal consumption. However, an increase in petroleum can be a threat to climate change. In contrast, renewable energy in the USA rose significantly compared to past years. Compared to 2015, with an increase of 7%, the USA generates 20% of electricity from renewable energy. Our forecasted results in the USA with the LSTM model also indicate a predictive path of USA's commitment to reducing $CO_2$, methane, and $N_2O$ emissions (see Fig. 5).

## Forecasting $CO_2$, methane, and $N_2O$ emissions in Russia

Finally, the algorithm was performed to examine Russia's $CO_2$, methane, and $N_2O$ emissions. Based on available data, Russia's $CO_2$, methane, and $N_2O$ emissions were reviewed from 1992 to 2018 and forecasted with LSTM from 2019 to 2023. The results presented in Fig. 6 show a dropped rate of $CO_2$ emissions from 2,005,430 kt in 1992 to 1,456,150 kt in 1999, then between 2000 and 2005, $CO_2$ emissions increased in Russia. After 2011, a continuous decline in $CO_2$ emission can be seen up to 2016 in Russia. Regarding coal and petroleum consumption, Russia used 7.41 quad Btu of coal in 1992 and 9.32 quad Btu of petroleum in 1992 to 5.30 quad Btu of coal in 2018 and 6.87 quad Btu of petroleum in 2018, respectively. The results presented in Fig. 6 show a downward trend of methane emissions from 1992 to 1999, then it increased gradually from 598,700 (thousand metric tons of $CO_2$ equivalent) in 2000 to 849,570 (thousand metric tons of $CO_2$ equivalent) in 2018. The statistical report shows that Russia consumed 16.61 quad Btu of natural gas in 1992, increasing gradually to 17.78 quad Btu in 2018. $N_2O$ emissions in the case of Russia show a continuous downward trend. In 1992, $N_2O$ emissions were recorded with a value of 88,490 (thousand metric tons of $CO_2$ equivalent), which dropped significantly over the years.

In the case of Russia, total energy consumption increased by 2.6% between 2015 and 2019, then continuously dropped by 5% in 2020. In 2020, 54% of energy consumption was represented by gas consumption, followed by coal, nuclear, hydro, and biomass, with 20%, 15%, 8%, 2%, and 1%,

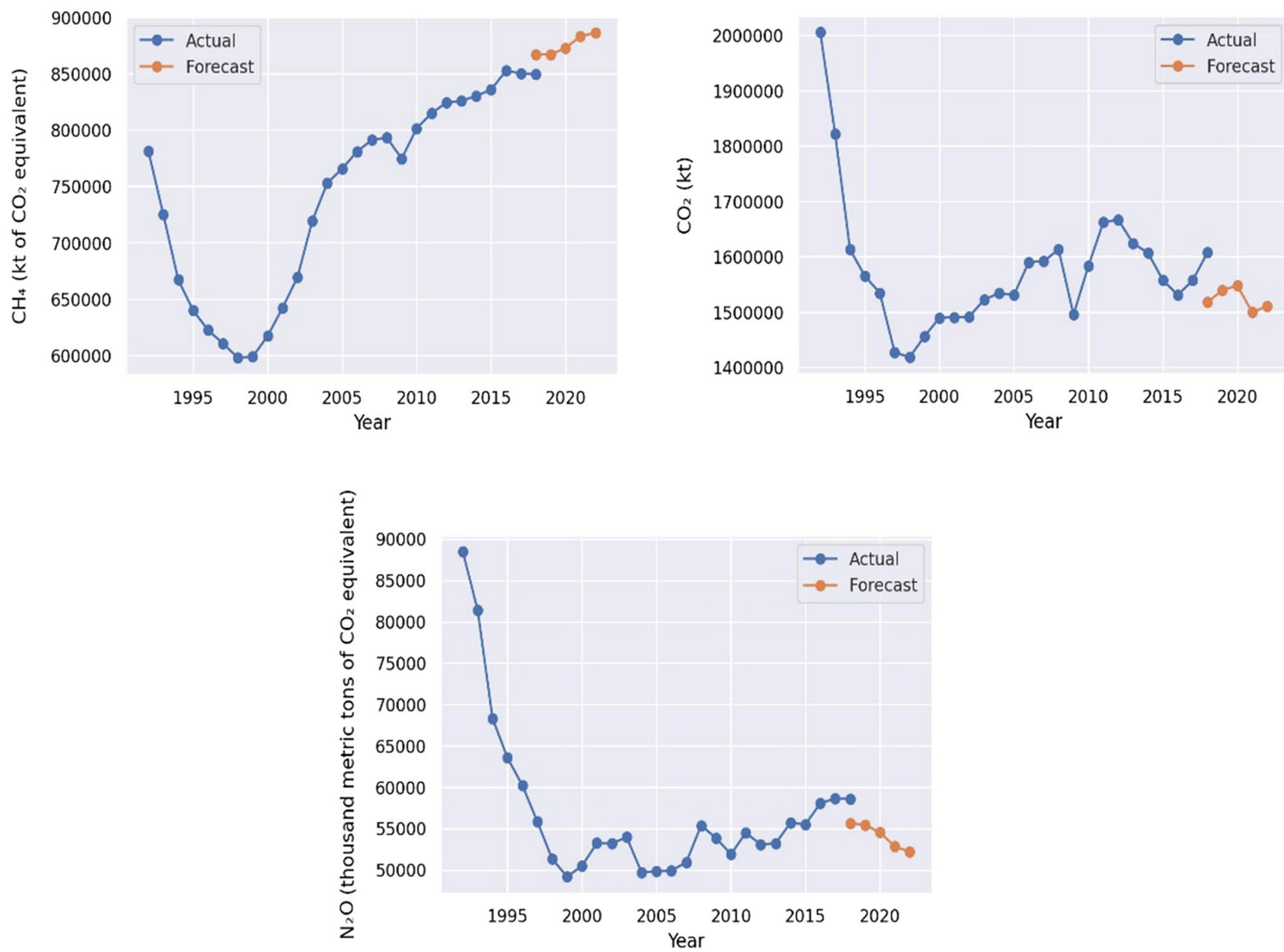



**Fig. 6** Yearly $CO_2$, methane and $N_2O$ emissions trend in Russia

respectively (Enerdata 2020). Besides, Russia is one of the largest crude oil producers globally, representing 512,358 kt of crude oil in 2020. This evidence shows that Russia's primary energy consumption depends on natural gas, coal, and other fossil fuels. According to the energy outlook in Russia (Enerdata 2020), natural gas represents 38% in the electricity sector, followed by 23% in the industrial sector and 18% in the residential territories. Consequently, the transportation sector consumes 39% of oil in Russia, followed by the industrial sector with 32%.

As shown in Fig. 6, $CO_2$ and $N_2O$ emissions significantly reduced over the years, and LSTM forecasted trend from 2019 to 2023 also indicates a slowdown of $CO_2$ and $N_2O$ emissions in Russia. However, the results indicate that methane emission is the highest one and can have negative consequences on climate change until fossils fuels such as natural gas, coal, and oil are the main sources of energy consumption in Russia. Therefore, Russia needs to revise energy policies and focus on the determinants linked with methane emission to mitigate environmental risk.

Overall, burning fossil fuels to meet increasing energy demands causes environmental degradation. The findings of the previous studies also confirmed that energy consumption causes environmental pollution (Saud et al. 2019). The results reported in the study (Sun et al. 2018) show that energy consumption and GDP impact carbon emissions in China. Consequently, another study concludes (Kanat et al. 2021) that higher consumption of fossil fuels such as coal, oil, and natural gas degrades the environment in Russia. The outcome of these findings is consistent with our analysis, as this study confirmed that a high volume of coal, petroleum, and natural gas increases greenhouse gas emissions. On the other hand, our results with the ML approach are in line with some studies. For suppose, the findings in the study of Magazzino et al. (2021) confirmed that India's carbon emissions have an increasing trend after 2019 and a slowdown in carbon emission for China. Further, their findings reported a decreasing trend in $CO_2$ emissions in the USA. Our findings also show India's dependency on fossil fuel consumption can further accelerate $CO_2$ emissions (Wang et al. 2020). In contrast, our results revealed an increasing trend of $CO_2$ emission in China. The Chinese economy has continued to grow, and to meet energy demands for commercial and industrial purposes, the country still uses a large volume of fossil fuels for energy consumption. The historical trend of energy consumption is also evident that coal has remained the major contributor to the energy mix in China. Hence, China's dependency on fossil fuel to meet energy demand can trigger greenhouse gas emissions. The findings of MK (2020) suggested that fossils fuel is a critical determinant to increase $CO_2$ emissions in India. Bakay and Ağbulut (2021) forecasted greenhouse gas emissions for Turkey. The results based on SVM, ANN, and deep learning confirmed that greenhouse gas emissions have an increasing rate due to the consumption of liquid fuels, coal, and other non-renewable fuels. Our findings support these results and further provide a detailed investigation of energy consumption in China, India, the USA, and Russia and subsequently highlight the increasing/decreasing trend of $CO_2$, methane, and $N_2O$ emissions.

## Conclusion

The present study aimed to investigate the energy consumption and greenhouse gas emissions trend in China (1980–2018), India (1980–2018), the USA (1980–2018), and Russia (1992–2018). Four input variables, coal, natural gas, petroleum, and renewable energy consumption, were used for greenhouse gas ($CO_2$, methane, and $N_2O$) emissions. This study adopts three popular ML algorithms (ANN, SVM, and LSTM) to predict $CO_2$, methane, and $N_2O$ emissions in China, India, the USA, and Russia from 2016 to 2018. Overall, the results indicate that the three ML algorithms have an excellent capability in predicting outcome variables. All the algorithms exhibited smaller RMSE, MAPE, and MBE; however, the performance success of the LSTM model compared to ANN and SVM was found more accurate. Furthermore, the LSTM model was performed to analyze a trend of $CO_2$, methane, and $N_2O$ emissions in China, India, the USA, and Russia from 2019 to 2023. The forecasted results with the LSTM model show an increase in $CO_2$, methane, and $N_2O$ emissions in China and India. The findings indicate a slowdown trend of $CO_2$, methane, and $N_2O$ emissions in the USA and Russia. The findings indicate that energy consumption is an important determinant of greenhouse gas emissions; notably, the study concluded that a large volume of coal, petroleum and natural gas degrades environmental quality. The varying results in the four countries demonstrate that the greenhouse gas emissions trend is upward for the country that uses higher coal, petroleum and natural gas. This relationship is a severe problem for global warming, climate change, and human health, as energy consumption with fossil fuels can increase environmental, economic, and health risks. On the opposite, the countries that use a lower volume of coal, petroleum and natural gas show a downward greenhouse gas emissions trend.

The historical trend of greenhouse gas emissions in China and India has been seen a continuous increase over the years. Besides, both countries depend on fossil fuel consumption; coal is the primary input source to meet energy demand in China and India. Similarly, the USA fulfills energy demand from petroleum, natural gas, and other fossil fuels, whereas Russia's energy consumption is dependent on natural gas. Energy consumption with fossil fuels to meet industries, commercials, and household demand are similar issues that further exacerbate environmental, social, and economic issues. These four countries are responsible for greenhouse gas emissions, accounting for 54% of $CO_2$ emissions in the global environment (EPA 2021); therefore, governments of these countries need to switch from fossils fuel consumption to renewable energy and accelerate clean energies consumptions. Since industrialization is crucial to economic development, however, producing goods with high carbon sources cannot be neglected; therefore, these countries need to strike a balance between industrialization and environmental survival.

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**Availability of data and materials** Supplementary data to this article will be provided on request.

## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

**Ethics approval** This article does not contain any studies with animals performed by any of the authors.

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