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Review Article

Analysis of the Strategic Emission-Based Energy Policies of Developing and Developed Economies with Twin Prediction Model

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Upholding sustainability in the use of energies for the increasing global industrial activity has been one of the priority agendas of the global leaders of the West and East. The projection of different GHGs has thus been the important policy agenda of the economies to justify the positions of their own as well as of others. Methane is one of the important components of GHGs, and its main sources of generation are the agriculture and livestock activities. Global diplomacy regarding the curtailment of the GHGs has set the target of reducing the levels of GHGs time to time, but the ground reality regarding the reduction is far away from the targets. Sometimes, the targets are fixed without the application of scientific methods. The aim of the present study is to examine sustainability of energy systems through the forecasting of the methane emission and agricultural output of the world's different income groups up to 2030 using the data for the period 1981–2012. The work is novel in two senses: the existing studies did not use both the Box–Jenkins and artificial neural network methods, and the present study covers all the major economic groups in the world which is unlike to any existing studies. Two methods are used for forecasting of the two. One is the Box–Jenkins method, where linear nature of the two variables is considered and the other is artificial neural network methods where nonlinear nature of the variables is also considered. The results show that, except the OECD group, all the remaining groups display increasing trends of methane emission, but unquestionably, all the groups display increasing trends of agricultural output, where middle- and upper middle-income groups hold the upper berths. The forecasted emission is justified to be sustainable in major groups under both methods of estimations since overall growth of agricultural output is greater than that of methane emission.

1. Introduction

From the last half of 19^{th} century to till date, economic growth turns into the most important particle of almost all socioeconomic systems in our mother earth. To achieve the higher growth trajectory, each and every economy put all of their resources on the board without giving any potentiality to future generations. It is only in late 90s, when scarcity of resources and a relatively new term "global warming" knocking the door of the policy and law makers around the world, human beings push forward the agenda of sustainability. In the wake of the issues related to sustainability, researchers are often engaged themselves in a debate over the existence of whether substitutability or complementarity are working between the association of growth and environment [1, 2].

It has been historically evidenced that growth can revolutionize the structural changes in both production and consumption. Such changes may occur from either directions or both, that is, either from level or composition or from both of them [3]. Interestingly, both the level and the composition of production and consumption activities affect environmental degradation and raise the scope of greenhouse gas (GHG) emissions, owing to which the prospects of sustainable economic development may hamper in future [4, 5]. It is evidenced that GHG contributes global warming and, consequently, generates severe environmental matters. It is to be noted that, to control the global emissions of GHG, the Kyoto Protocol was proposed and signed by almost all the countries in the world. The Kyoto Protocol specified six GHGs, including methane (CH_4), carbon dioxide (CO_2), nitrous oxide (N_2O), perfluorocarbons (PFCS), hydrofluorocarbons (HFCS), and sulphur hexafluoride (SF_6) [6]. In 2014, the concentration of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) in the atmosphere was 397.7 ppm, 1833 ppb, and 325.9 ppb, respectively (World Meteorological Organization, 2015). On the average, the anthropogenic emissions grew 1.3% annually from 1970 to 2000 and 2.2% annually from 2000 to 2010 [7]. Moreover, after carbon dioxide, methane is the second most emitted GHG; its potential to catch heat in the atmosphere is 23 times higher than carbon dioxide [8] and so a clinical examination on increase in methane gas emission needs more attention.

Under 1996 IPCC revised guidelines, national GHG inventories includes energy, industrial process, solvent and other products, agriculture, land-use change and forestry, and waste, while the above-stated list is modified under 2006 IPCC guidelines [6, 9, 10]. Following the just-stated segregation of GHG, methane emissions are also generated from several production sectors. For instance, anthropogenic methane is emitted from sectors like cattle breeding, rice cultivation, extraction and transport of fossil fuels, and waste management [11]. These emissions result from very heterogeneous processes with several scopes for abatement. Accordingly, existing heterogeneity of production structures across countries introduces cross-country asymmetries broadly based on agriculture-based methane or industry-based methane emissions. Interestingly, methane emission and sectoral composition are rarely analyzed in the literature. However, such gap is widened enough in case of agricultural methane emissions. Methane is produced and emitted from the decomposition of livestock manure and the organic components in agro-industrial wastewater. These wastes are typically stored or treated in waste management systems that promote anaerobic conditions and produce biogas, a mixture of about 70 percent methane, 30 percent carbon dioxide, and less than 1 percent hydrogen sulfide. Globally, manure management added an approximated 237 million metric tons of carbon dioxide equivalent of methane emissions in 2010, roughly 4 percent of total anthropogenic methane emissions. Out of total emitted agro-based methane, almost 85 percent is accompanied by USA, China, and India together, followed by Brazil, Pakistan, and Vietnam [12]. It is to be noted that the agriculture methane may emit also from nations which use more capital-intensive production technique, and hence, a critical analysis between agriculture and methane emissions is needed abruptly.

Amalgamation of methane emission with agriculture production creates doubt over the efficacy of sustainability issue. Massive agriculture production can emit more vulnerable methane along with other GHGs. Again, such methane emissions may affect weather variability and multiply climate change risks and the magnitude of global warming. This can affect dairy cattle feeding sector along with other agriculture-based activities more severely. As a consequence, the vulnerability of agriculture-based livelihoods may increase with induced disaster risks. However, there is no definite and robust model which can estimate social costs from such emissions [13]. Hence, by minimizing environmental degradation and pollution risks along with adaptation to climate and weather, variability risks should not only increase resilience of farmers' production systems but also stabilize their output and income [14]. Identification and reduction of above-stated uncertainties and risk factors in terms of anticipatory adaptation may raise the potentiality of sustainability paradigm [15]. Therefore, climate change adaptation policies in the agricultural sector along with adaptation to control methane emission are to be implemented for getting sustainable development. Therefore, the question still remains in mind: "does complementarity between methane emission and agriculture production generate sustainability?" This paper also tries to locate, screen, and evaluate this issue for major income groups of the world.

This paper contributes original findings concerning methane emission and agriculture production with special emphasis on sustainability. First, it goes for forecasting of methane emission and agricultural output using the Box–Jenkins (BJ) and artificial neural network (ANN) methods. Second, it goes for testing the sustainability of methane emission vis-à-vis agricultural output.

The paper is organized as follows: literature review is presented first, followed by data, methodology, analysis of results, and conclusion.

2. Literature Review

Table 1 exhibits the brief information on the highly relevant works reviewed so far for the present study.

Analysis related to GHG emission and economic activities are not new in the literature. Study related to GHG emission and economic growth has been discussed in the literature quite rigorously [16–19]. All these studies used the similar kinds of methodology to relate GHG emission with growth. In fact, these studies have used CO_2 as a measure of GHG and per capita income for panel data to show the presence of EKC. Again, there are a few studies that have used several GHGs, and they have confirmed the existence of EKC for methane emissions [20–22]. In this context, using a dataset for 22 OECD countries, it has shown a quadratic relationship between methane emission and GDP in the long run [20]. Such quadratic relationship between methane emission and GDP has also been established in the literature for different datasets [22]. Again, industrial methane emission of 39 countries explicitly claims N-shaped relationship between the methane emission and economic growth [21].

In a notable working series titled "OECD Environmental Outlook to 2030," it studies the prediction of GHG emissions in 2030 if the present inaction on environment remains unchanged [24]. The report reveals that, by 2030, the world economy is expected to nearly double and world population

Table 1: List of relevant studies reviewed.

Article	Year	Link with present study	Methodology	Outcomes
Acaravci and Ozturk [16]	2010	This study examines the causal relationship between GHGs, energy consumption, and economic growth	Uses autoregressive distributed lag (ARDL) bounds testing approach of cointegration for nineteen European countries	Shows long-run relationship between GHGs, energy consumption per capita, real GDP per capita, and the square of per capita real GDP
Apergis and Ozturk [17]	2015	This study focuses on both GDP and policies in fourteen Asian countries to capture income-emission relationship	Uses GMM method to a multivariate panel data framework	Illustrates inverted U-shaped association between emissions and per capita GDP for selected Asian economies over the period 1990–2011
Coondoo and Dinda [18]	2002	This study presents the results of a study of income and major GHG emission	Granger causality test is used to cross-country panel data on per capita income and the corresponding per capita CO_2 emission	For the group of developed economies, the causality is found to run from GHG emission in terms of CO_2 emission to income
Kasman and Duman [19]	2015	This article examines the causal relationship among energy consumption, carbon dioxide emissions, economic growth, trade openness, and urbanization for a panel of new EU member and candidate countries	Panel cointegration methods and panel causality tests are used to investigate such associations	Short-run unidirectional panel causality running from energy consumption, trade openness, and urbanization to carbon emissions and long-run associations are claimed
Cho et al. [20]	2014	This study investigates the EKC hypothesis by using the total GHG and methane emission	Uses panel cointegration tests as well as the fully modified ordinary least squares (FMOLS) approach	Shows that a quadratic relationship may exist in the long run for twenty-two OECD countries
Fujii and Managi [21]	2016	This study analyzes the relationship between economic growth and emissions of major GHGs including methane	Uses of both time series and panel data analysis	Shows doubt over presence of EKC for several individual industries and illustrates the presence of EKC at the country and total industrial sector level data
Kubicová [22]	2014	Examines both EKC and PHH in the context of GHGs for Slovak Republic	Granger causality test	Concludes that the volume of per capita per capita greenhouse gas emissions in the present period and in any of the previous four periods has no effect on the amount of net FDI inflows as a percentage of GDP in the Slovak Republic
Marchal et al. [23]	2011	This study searches for the policy implications of the climate change challenge in the context of methane emission and growth	Cross-sectional data and forecasting method are used	Methane and nitrous oxide emissions are projected to increase to 2050; although agricultural land is expected to expand slowly along with the escalation of agricultural productions in developing countries
OECDEO [24]	2008	This study predict the GHGs emissions in 2030 under unchanged environmental conditions	Employs simulations exercise in order to find policy actions to address the key challenges, including their potential environmental, economic and social impacts	Claims a rise in income and aspirations for better living standards will increase the pressure on the planet's natural resources
Ali and Abdullah [25]	2015	This study examines the association between the major GHG emission and its determinants like economic growth, financial development, and trade openness for the time period 1970–2012	Uses vector error correction model (VECM) approach to investigate the relationship between the variables	Claims economic growth, financial development, and trade openness are still very important in determining the CO_2 emissions
Benavides et al. [26]	2017	This study investigates the relationship between methane emissions, GDP, electricity production from renewable energy sources, and trade openness	Uses ARDL and Granger causality test	Shows unidirectional causality between CH_4 and the variables involved

Table 1: Continued.

Article	Year	Link with present study	Methodology	Outcomes
Du et al. [27]	2018	Illustrates methane emissions from 2000 to 2014 that originated from wastewater from different provinces in China	Adopts artificial neural network model	Shows an increasing trend in methane emissions in China and a spatial transition of industrial wastewater emissions
Fernández-Amador et al. [28]	2018	Estimates the income elasticity of per capita methane emissions	Uses threshold models with piecewise-linear income elasticity	Income elasticity decreases at high income levels but the rate is diminishing
Shahbaz et al. [29]	2015	Examines the EKC hypothesis in Portugal in the context of major GHG emission	Adopts ARDL bounds testing approach	Shows existence of EKC hypothesis in both the short run and long run
Shahbaz et al. [30]	2014	Investigates the existence of EKC hypotheses in case of Tunisia using annual time series data for the period of 1971–2010	ARDL bounds testing approach, vector error correction model, and innovative accounting approach are employed	Claims long run association among economic growth, energy consumption, trade openness, and CO_2 emissions
Bates [31]	2001	Considers agriculture GHG emission with reference to methane and nitrous oxide emissions in EU	Time series and panel data analysis are used	Predicts that the baseline emissions of methane and nitrous oxide in the agricultural sector are likely to decline by 7%
Fernández-Amador et al. [11]	2018	Considers global dataset on methane inventories derived from production, final production, and consumption for the time period 1997–2011	Uses panel data regression	Shows the presence of relative decoupling between methane and growth, and the relationship is nonlinear in nature
Hasegawa and Matsuoka [32]	2010	Introduces an integrated model to predict global CH_4 and N_2O emissions and reduction potentials related to agricultural production over the period 2000 to 2030	Agricultural model and countermeasure selection model are introduced	Claims that the livestock manure management and rice paddy are expected to be emission sources that have high reduction potentials
Adger et al. [33]	2005	This study reviews the nature of adaptation and also examines the implications of different spatial scales for these processes	Uses normative evaluative criteria	Shows that elements of effectiveness, efficiency, equity, and authenticity are important in claiming success in terms of the sustainability
Asghar et al. [34]	2006	Introduces the ideas of disasters management with GHG emission	Model of integrated disaster management is used	Findings have claimed that proper policy investigations, plans, programmes and adaptation in terms of risks, and opportunities can make GHG emissions as sustainability indicators
Barnett and O'Neill [35]	2010	Relates adaptation and GHGs in the context of Melbourne	Considers comparative analysis	Claims in favour of introduction a line of investigation that the policy-makers should ask and seek answers before committing resources to adaptation decisions
Haddad [14]	2005	Relates HDI with GHGs	Introduces sociopolitical model	Advocates that adaptive capacity based on national sociopolitical aspirations is needed
Maredia and Minde [36]	2002	Examines association among agriculture, technology, and environmental degradation	Uses Africa-based analysis with descriptive statistics	Finds lack of adaptation may degrade environment with more higher agricultural productivity in Africa
Mimura et al. [37]	2014	Relates adaptation with climate change	Adaptation strategy is employed	Recognizing the importance of mainstreaming adaptation and the integration of adaptation policies within those of development increases
Volenzo [38]	2015	Relates methane emission, agriculture, and adaptation	Simulation exercises has been introduced	Claims failure to adopt proper adaptation may aggravate small-scale farmers' vulnerability to climate change and weather variability and in return economy will produce suboptimal outcomes

Table 1: Continued.

Article	Year	Link with present study	Methodology	Outcomes
Volenzo et al. [39]	2019	Related to methane emission, agriculture, and adaptation	Uses simulation exercises	Encouraged to design and implement policies and strategies that take cognizance of poverty-maladaptation-environmental degradation nexus

to grow from 6.5 billion today to over 8.2 billion. Most of the growths in income and population will be in the emerging economies of Brazil, Russia, India, Indonesia, China, and South Africa (the BRIICS) and in other developing countries. Rising income and aspirations for better living standards will increase the pressure on the planet's natural resources. In another series titled "OECD Environmental Outlook to 2050," it envisages that, without more ambitious policies than those in force today, GHG emissions will increase by another 50% by 2050, primarily driven by a projected 70% growth in CO_2 emissions from energy use [23]. This is primarily due to a projected 80% increase in global energy demand. Furthermore, it claims that, historically, although OECD economies have been responsible for most of the emissions, in the coming decades, increasing emissions will also be caused by high economic growth in some of the major emerging economies. Again, global energy-related carbon dioxide (CO_2) emissions are projected to increase by one-third between 2012 and 2040. The continuing increase in total emissions occurs despite a moderate decrease in the carbon intensity (CO_2 per unit of energy) of the global energy supply [40].

From the international trade angle, a few studies have found positive relationship between trade openness and CO_2 emissions [25, 29, 30]. Positive association between methane emission and trade openness is also acknowledged in the literature [26]. Moreover, economic growth and several socioeconomic activities are claimed responsible for methane emission [25]. In fact, rapid growth, population size, and foreign direct investment are made as the responsible factors behind methane emission for different cross-sections [30]. Again, through an interesting study, it is reported that the elasticity of methane emissions with respect to income per capita income is low and it may decrease over time [28]. In a recent study based on country specific efforts, it has been calculated by neural network method that the predicted methane emission from wastewater in China will be an increasing trend and a spatial transition of industrial wastewater emissions from eastern and southern regions to central and southwestern regions and from coastal regions to inland regions will occur [27].

Again, some studies are focused on the reduction potentiality of methane emission from agriculture [31, 41]. Usually, such studies have used static methodology and derived short-run estimates to locate the reduction possibility of methane emission from agricultural sector [31, 41]. However, long-run analysis has also been established, in which methane emissions from agriculture and reduction prospective under several marginal abatement costs, huge drop likely regions, and emission sources are claimed for long-run [32]. Again, establishing the significance of agricultural sector in the context of GHGs emission, it has been claimed that the anthropogenic methane emissions are mostly produced by a few economic sectors such as cattle breeding and rice cultivation [11].

Issues related to sustainable development in the context of agriculture production and methane gas emission have been discussed critically in the literature. Furthermore, it is argued that proper policy investigations, plans, programmes, and adaptation in terms of risks and opportunities can make GHG emissions as sustainability indicators to uphold sustainable development [34, 42]. To get sustainability, investigators are usually advocated for the attractive adaptation measures to pursue efficiently in long run [37]. Investigation in this aspect has revealed that, by controlling environmental degradation and pollution risks along with adaptation to climate and weather, variability risks may increase resilience of farmers' production systems and also side by side stabilize their output and income [14]. In another series titled "Sendai framework for disaster risk reduction 2015–2030," it has been argued that minimization of uncertainties and risk factors owing to climate change attached to agriculture can be optimized through anticipatory adaptation [15]. Sustainable development in terms of improvement of farmer's livelihood is claimed and argued in favour of proper adaptation of changing policy regimes in the context of environmental degradation to opt sustainability [36]. Again, with inability to screen, evaluate, and treat risks augmented in dairy feeding, adaptation initiatives are declared as responsible factors to enhance risks embedded in climate change. Furthermore, studies claim that just-stated failure to adopt proper adaptation may aggravate small-scale farmers' vulnerability to climate change and weather variability, and in return, economy will produce suboptimal outcomes [33, 35, 38]. In a more recent study, it has been claimed that methane gas emission along with other GHGs emissions from agriculture production and in dairy feeding strategies can be used as a measure and indicator of sustainability. It has been further argued that policy implementation to curb risks associated with agriculture production owing to methane emission must be embedded with the cognizance of poverty, maladaptation, and environmental degradation nexus [39].

3. Rationale of the Present Study

The review of literature highlights different aspects of GHG emission in general and methane emission in particular and their impacts in different sectors of different economies but does not cover studies related to forecasting of methane emission in world's leading methane emitting countries. The present study has tried to fill the gap in the literature by means of forecasting methane emission for world's leading economic groups up to the year 2030. Furthermore, the sustainability of the forecast values of methane emission has been analyzed by means of forecast values of agricultural output of the same economic groups. It is thus a novel work in our view.

3.1. Data. The study uses the time series data on methane emission (in kt CO_2 equivalent) for the five groups of economies (high income, upper middle income, middle income, lower middle income, and low income) for the period 1981–2012. It also uses the time series data for the same period and same groups of economies on the total agricultural value added measured in current USD. Both the data series are borrowed from the World Bank (http://www.wordbank.org).

3.2. Methodology. Twin methods, not actually hybrid in usual sense, are used for forecasting of methane emission and agricultural value added. One is the Box–Jenkins method, where linear nature of the two variables is considered, and the other is artificial neural network methods, where nonlinear nature of the variables is also considered.

3.3. Box–Jenkins Method of Forecasting. Before going into the details of Box and Jenkins method of forecasting, we need to see how a time series data of a particular variable is generated.

There are three processes behind generation of a time series data:

(1) AR process: past values of the variable and error term generate the data

(2) MA process: only the errors or the disturbance term generate the data

(3) ARMA process: data are generated by the combination of AR and MA processes

Sometimes, it is taken as ARIMA model, where "*I*" stands for integration of the series or how many differencing is done for making the time series of the variable to stationary.

In the AR (p) process, the current value of a variable "y" depends on only the past values plus an error term. If there are "p order in the process, i.e., the current value of y depends on the p order of past values and an error term of the current period," then the AR(p) can be written as

$$y_t = \mu + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \varphi_3 y_{t-3} + \varphi_4 y_{t-4} + \cdots + \varphi_p y_{t-p} + u_t = \mu + \Sigma \varphi_i y_{t-i} + u_t, \quad (1)$$

where u_t is the white noise (WN) error term with zero mean, constant variance, and zero auto-covariance.

On the contrary, an MA(q) process is the linear combination of all the "q" terms of white noise terms depending on time. It is a white noise process in which the current value of y_t depends on the current value of the WN error term and all past values of the error terms. Because all the errors are WN, an MA process is necessarily a stationary process further because it is the linear combination of all plus and minus values of the errors which hover around zero.

So, an MA (q) process can be written as

$$\begin{aligned} y_t &= u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \theta_3 u_{t-3} + \theta_4 u_{t-4} + \cdots + \theta_q u_{t-q} \\ &= u_t + \sum \theta_i u_{t-i}. \end{aligned} \quad (2)$$

An AR process is stationary if the characteristic root lies outside the unit circle or having values >1, then φ becomes less than 1. This means the condition $\varphi < 1$ leads to the values lying inside the unit circle representing stationarity of the AR process, and the model will thus have stability property.

An ARIMA (p, q) process is the combination of AR and MA processes, "*I*" being the order of integration, which can be represented by "d," number of differencing to convert the series from nonstationary to stationary. The model for ARMA (p, d, q) can then be written as

$$\begin{aligned} y_t = \mu &+ \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \varphi_3 y_{t-3} + \varphi_4 y_{t-4} + \cdots + \varphi_p y_{t-p} \\ &+ u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \theta_3 u_{t-3} + \theta_4 u_{t-4} + \cdots + \theta_q u_{t-q}. \end{aligned} \quad (3)$$

Using Lag operator, we have

$$\begin{gathered} \left(1 - \varphi_1 L - \varphi_2 L^2 - \varphi_3 L^3 - \varphi_4 L^4 - \cdots - \varphi_p L^p\right) y_t = \mu + \left(1 + \theta_1 L + \theta_2 L^2 + \theta_3 L^3 + \theta_4 L^4 + \cdots + \theta_q L^q\right) u_t \; Or, \\ \varphi(L) y_t = \mu + \theta(L) u_t. \end{gathered} \quad (4)$$

This relation stands for invertibility between the AR and the MA process.

3.4. Forecasting in ARIMA Model: Box–Jenkins Method. The BJ methodology to determine which model is appropriate follows a four-step procedure:

Step 1: identification: to determine the appropriate values of p, d, and q.

(i) The main tools in this search are the correlogram and partial correlogram.

Step 2: estimation: to estimate the parameters of the chosen model.

Step 3: diagnostic checking: to check if the residuals from the fitted model are white noise.

(i) If they are, accept the chosen model; if not, start afresh.
(ii) That is why the BJ methodology is an *iterative process.*

Step 4: forecasting. The ultimate test of a successful ARIMA model lies in its forecasting performance, within the sample period as well as outside the sample period. On the basis of the acceptable results obtained from steps 1 to 3, forecasting is made on the appropriate model of ARIMA. The forecasting results are accepted on the basis of the acceptable values of root mean square error (RMSE), bias proportion, variance proportions, and covariance proportions. The acceptable forecasted values will be those whose RMSE will be minimum possible, and covariance proportions will be greater than bias proportions and variance proportions.

4. Methodology of ANN-Based NAR

Real-world data always contains nonlinearity, and specifically, its behaviour is dynamic and depends on their current period. Under such circumstances, the nonlinear autoregressive (NAR) neural network structure is effective to make efficient prediction about future [43]. The first advantage of NAR networks is that they can accept dynamic inputs represented by time series sets. Time series forecasting using a neural network is a nonparametric method, which implies that knowledge of the process that causes the time series is not necessary. Moreover, the NAR model utilizes the past values of the time series to predict future values. This fact makes it hard to model time series using a linear model; therefore, a nonlinear approach should be preferred, and the present study has also attempted the method. A nonlinear autoregressive neural network, applied to time series forecasting, describes a discrete, nonlinear, autoregressive model that can be expressed in the following manner [44, 45]:

$$x(t) = f(x(t-1), x(t-2), x(t-3), \ldots\ldots, x(t-q)) + v(t), \quad (5)$$

where $x(t)$ is data series of x variable at time t; $f(.)$ is unknown in advance, and the training of the neural network aims to approximate the function by means of the optimization of the network weights and neuron bias; and $v(t)$ is the error of the approximation of x at time t.

This training function is often operated efficiently with backpropagation-type algorithm, and to perform this with our stated $f(.)$, we use Levenberg–Marquardt backpropagation procedure (LMBP) [46, 47] to solve any specified NAR neural network. In Figure 1, we present the topology of a standard NAR network.

After getting the forecasted values of both the series for methane emission and agricultural value added up to the year 2030, we try to test whether the forecasted methane emission is sustainable by means of looking at the forecasted values in agricultural outputs for the selected five groups of economies. For this purpose, we have first calculated the growth of these two indicators over the forecast period and average values of these two growth rates for all the groups. After that, we have tested the mean difference of these two indicators, methane emission and agricultural value added, and tested their significance statistically. If the average growth of agricultural output is tested to be greater than that of methane emission, then it may be said that the emission is sustainable as it contributes positively and largely to agricultural output. The reverse results may say the unsustainable methane emission in the forecasted period.

4.1. Analysis of Results. As mentioned earlier, the study applies Box–Jenkins (BJ) and artificial neural network (ANN) for forecasting methane emission and agriculture output for the period 2013–2030 on the basis of data for the period 1981–2012. The results of both the methods are given one by one.

4.1.1. Forecasting by Box–Jenkins Method. For the BJ method, the following four steps are followed which are mentioned in Methodology:

Step 1: identification: to determine the appropriate values of p, d, and q, we have done unit root test through ADF test and correlogram methods. The results for both the series are presented in Tables 2 and 3. Looking at the autocorrelation functions (ACFs) and partial autocorrelation functions (PACFs), we have identified the orders of AR and MA processes. There may be more than one alternative of the shapes of ACF and PACF, and we will have to determine the optimum structure of ARIMA. For this purpose, steps 2 and 3 are followed.

Step 2: estimation: to estimate the parameters of the chosen model, we run equation (4).

Step 3: diagnostic checking: to check if the residuals from the fitted model are white noise. The acceptable regression results are taken on the basis of where both AR and MA coefficients are significant, adjusted R^2 is highest, and information criteria (AIC and SIC) are of lowest values. The results of steps 1 to 3 are given in Table 2 for methane emission and in Table 2 for agriculture output for all the groups of economies. The roots of the AR and MA should lie inside the unit circle, indicating stability of the models.

Let us first discuss the results (for steps 1 to 3) on the methane emission with the help of Table 2. The results from the table show that, in all the groups of economies, the series are integrated of order 1. The optimum orders of the autoregressive and moving average terms are marked bold. They are (4, 4) for the OECD and lower middle group, (11, 11) for the upper middle group, (6, 6) for the middle group, and (1, 1) for the low group. And all of these terms are less than unity in values, indicating the stability of the models.

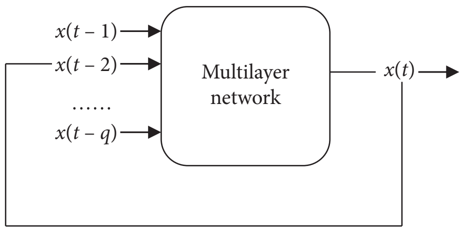

Figure 1: Nonlinear autoregressive neural network.

Now come to the discussion on the results (for steps 1 to 3) of agriculture output with the help of Table 3. The results from the table show that, in all the groups of economies, the series are integrated of order 1. The optimum orders of the AR and MA terms are marked bold. They are (2, 12) for the OECD group, (4, 1) for the upper middle group, (3, 1) for the middle group, (3, 3) for the lower middle group, and (1, 1) for the low group. And the models in all the groups are stable.

Step 4: forecasting: on the basis of the acceptable results obtained from steps 1 to 3, forecasting is made on the appropriate model of ARIMA. The forecasting results are accepted on the basis of the acceptable values of root mean square error (RMSE), bias proportion, variance proportions, and covariance proportions. Figures 2 and 3 present the graphical plots of forecasted values of methane emission and agricultural output, respectively. The numerical values of the two forecasted series are given in the Appendix (Tables 4 and 5).

It is observed from Figure 2 that, except the OECD group, all the remaining four groups of economies demonstrate rising trends of forecasted values of methane emission. Middle-income group leads the club followed by the upper middle-income group and low-income group. The lower middle-income group maintains a constant forecasted path for the entire period of prediction. The positive improvements are observed only for the countries in the OECD group. The results thus show that the agriculture activity in particular and all the economic activity in general is not going to put pressure on the pollution level measured by methane emission for the developed countries, whereas the countries in the remaining world are going to pollute the environment. The derived forecasted values of methane emission have maintained the desirable properties of forecasting as their RMSE is low and the covariance proportions are greater than the bias and variance proportions (the results are not shown to avoid crowding of figures and tables in the text).

On the contrary, the forecasted values of agricultural value added for all the groups under the BJ method, as depicted in Figure 3 and Table 5, show rising trends for all up to 2030. But the difference is observed in their relative positions. The middle-income group is at the top, followed by the upper middle-, lower middle-, OECD, and low-income group. The rate of growth is steeper for the middle-income group as well.

4.1.2. Forecasting by ANN-Based NAR. In the ANN method, only one hidden layer has been used while number of neurons in hidden layer has been varied at four levels (5, 10, 15, and 20 number of neurons). Our experiments suggest employing 2 feedback delays of the variables for model building. Here, we have used backpropagation algorithm proposed by Levenberg–Marquardt for training. Figures 4 and 5, respectively, present the predicted values of methane emission and agriculture output. The quantitative figures for both are presented in the Appendix (Tables 6 and 7).

It is observed from Figure 4 that the OECD group demonstrates falling trend of the predicted methane emission, while the other four groups from low- to upper middle-income countries produce rising trends of the said emission. Furthermore, it is to note that the results under the ANN method are similar to that under the BJ method.

Figure 5 depicts that all the groups' predicted trends of agriculture output are upward rising over time which are alike to that under BJ method. But a little difference under ANN is observed for the OECD group as it turned downward trend after 2015.

Hence, the two methods of forecasting by and large produce the same results for both methane emission and agricultural output for all the groups of economies. Whatever differences observed are due to the differences in methodological structures. As mentioned in related literature [48–50] that the ANN is applied for linear and nonlinear data and BJ only for linear data, the former one can be used as better predictor for a dynamic variable like methane emission. As having association between methane emission and agricultural output, it is now required to examine whether the predicted methane emission is sustainable for all the groups for the period 2013–2030. This is the second objective of the study.

One way of examining such sustainability is to see whether growth of the predicted agricultural output is greater than that of methane emission. In other words, whether good economic effect is greater than bad pollution effect. For the said purpose, we have calculated the average growth rates of predicted methane emission and agricultural output and took their difference and test statistically (by t-test) whether such mean difference is positive statistically. We have done these tests for all the groups of economies separately for BJ and ANN results. The test results are given in Table 8.

It is observed from both the two methods of forecasting that the average growth for predicted methane emission is negative for the OECD group and positive for all the remaining four groups. Furthermore, the average growth of agricultural output is greater than that of the methane emission for all the groups of economies. The correlation between the growth of methane emission and that of agriculture output is positive and significant for all in case of the BJ method, but the correlation result is not significant for all the groups in case of the ANN method.

The results for mean difference test are positive and significant under the BJ method for all the groups which mean that the forecasted values of agriculture output are significantly greater than that of methane emission. This

Table 2: Unit root test and ARIMA results for methane emission.

Groups	ADF	Possible forms of ARIMA	Regression coefficients (prob)	$\bar{R}^2$	AIC	SIC
26 OECD	−5.83 (0.00)	(2, 1, 2)	AR(2) = −0.67 (0.00) MA(2) = 0.71(0.05)	0.14	21.79	21.83
		(4, 1, 4)	**AR(4) = 0.50 (0.00) MA(4) = −0.91(0.02)**	0.27	21.5	21.65
		(11, 1, 11)	AR(11) = −0.17(0.23) MA(11) = 0.87 (0.05)	0.62	20.6	20.75
Upper middle income	−4.11(0.00)	(3, 1, 4)	AR(3) = 0.39 (0.02) MA(4) = −0.24 (0.22)	0.07	25.05	25.19
		(11, 1, 11)	**AR(11) = −0.8(0.01) MA(11) = −0.94 (0.00)**	0.91	22.84	22.99
Middle income	−8.15(0.00)	(1, 1, 6)	AR(1) = −0.18 (0.35) MA(6) = −0.16 (0.42)	0.001	27.33	27.47
		(6, 1, 6)	**AR(6) = −0.57 (0.00) MA(6) = 0.96(0.00)**	0.38	26.96	27.11
		(15, 1, 15)	AR(15) = 0.01 (0.48) MA(15) = −0.99 (0.02)	0.99	7.64	7.78
Lower middle income	−8.5(0.00)	(1, 1, 4)	AR(1) = −0.38 (0.00) MA(4) = −0.08 (0.24)	0.12	27.31	27.45
		(4, 1, 4)	**AR(4) = 0.6 (0.02) MA(4) = −0.94(0.01)**	0.15	27.30	27.42
		(15, 1, 4)	AR(15) = 0.15 (0.16) MA(4) = −0.94 (0.01)	0.77	26.48	26.49
Low income	−7.37 (0.00)	(1, 1, 1)	**AR(1) = 0.45 (0.00) MA(1) = −0.99 (0.01)**	0.24	24.68	24.82
		(1, 1, 4)	AR(1) = −0.31 (0.28) MA(4) = −0.17 (0.21)	0.05	24.89	25.03

Note. Bold marks indicate significant results and the accepted ARIMA structures for which forecasting is made. Source: computed by the authors.

Table 3: Unit root test and ARIMA results for agricultural value addition.

Groups	ADF	Possible forms of ARIMA	Regression coefficients (prob)	R^2	AIC	SIC
26 OECD	−5.81 (0.00)	(2, 1, 2)	AR(2) = 0.18 (0.36) MA(2) = −0.99 (0.04)	0.33	51.48	51.62
		(2, 1, 12)	**AR(2) = −0.47 (0.00) MA(12) = −0.89(0.02)**	0.65	50.81	50.95
		(13, 1, 12)	AR(13) = −0.62(0.00) MA(12) = −0.88 (0.05)	0.70	50.85	51.01
Upper middle income	−4.11(0.00)	(1, 1, 1)	AR(1) = 0.95 (0.02) MA(1) = −0.66 (0.00)	0.33	52.26	52.4
		(1, 1, 3)	AR(1) = 0.47 (0.03) MA(3) = 0.39 (0.01)	0.34	52.25	52.39
		(3, 1, 1)	AR(3) = 0.71 (0.00) MA(1) = 0.31 (0.22)	0.38	52.24	52.38
		(3, 1, 3)	AR(3) = 0.78 (0.32) MA(3) = −0.06 (0.22)	0.34	52.4	52.54
		(4, 1, 1)	**AR(4) = 0.67 (0.01) MA(1) = 0.57 (0.00)**	0.36	52.24	52.38
		(4, 1, 3)	AR(4) = 0.52 (0.01) MA(3) = 0.33 (0.20)	0.29	52.41	52.56
Middle income	−8.15(0.00)	(1, 1, 1)	AR(1) = 0.98 (0.02) MA(1) = −0.68 (0.00)	0.40	52.96	53.1
		(3, 1, 1)	**AR(3) = 0.80 (0.00) MA(1) = 0.37 (0.00)**	0.48	52.87	53.01
		(3, 1, 3)	AR(3) = 0.93 (0.04) MA(3) = −0.08 (0.22)	0.45	52.93	53.00
Lower middle income	−8.5(0.00)	(1, 1, 1)	AR(1) = 0.91 (0.02) MA(1) = −0.58 (0.24)	0.35	51.09	51.23
		(3, 1, 1)	AR(3) = 0.82 (0.00) MA(1) = 0.29 (0.38)	0.45	50.96	51.10
		(3, 1, 3)	**AR(3) = 0.61 (0.04) MA(3) = 0.46 (0.02)**	0.46	50.94	51.08
Low income	−7.37 (0.00)	(1, 1, 1)	**AR(1) = 0.95 (0.00) MA(1) = −0.67 (0.01)**	0.30	47.3	47.44
		(2, 1, 1)	AR(2) = 0.36 (0.28) MA(1) = 0.4 (0.01)	0.16	47.5	47.64
		(3, 1, 1)	AR(3) = 0.9 (0.38) MA(1) = 0.18 (0.31)	0.16	47.5	47.64
		(4, 1, 1)	AR(4) = 0.35 (0.28) MA(1) = 0.19 (0.21)	0.14	47.57	47.61

Note. Bold marks indicate significant results and the accepted ARIMA structures for which forecasting is made. Source: computed by the authors.

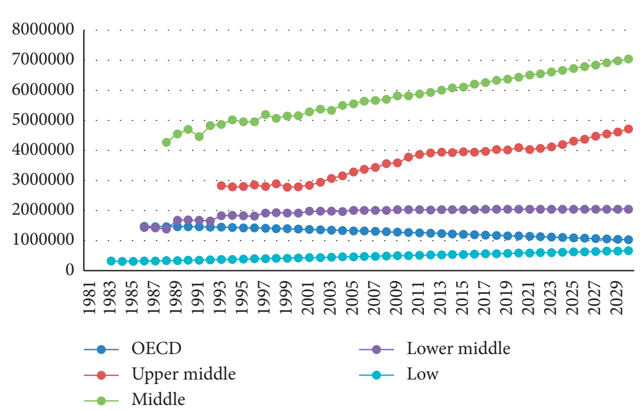

Figure 2: Forecasted values of methane emission (in kt of equivalent CO_2) under the BJ method. Source: drawn by the authors.

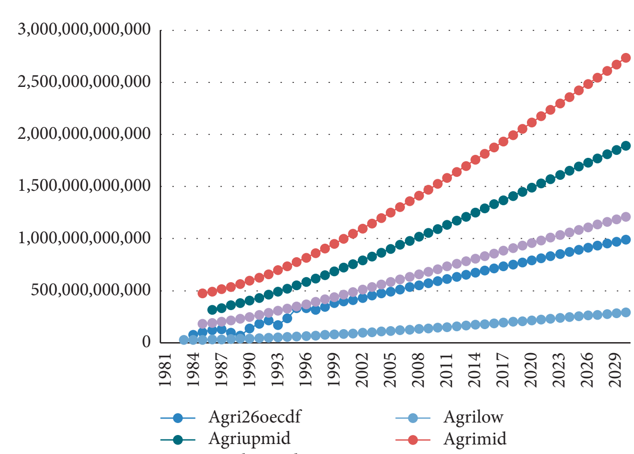

Figure 3: Forecasted values of agriculture output (in current USD) by the BJ method. Source: drawn by the authors.

Table 4: Forecasted values of methane emission (in kt CO_2 equivalent) under the BJ method.

	OECD	Upper middle	Middle	Lower middle	Low
1981					
1982					
1983					319376.7
1984					310579.6
1985					310981.8
1986	1473936			1441004.78	315518.4
1987	1465419			1417409.14	321913
1988	1463133		4266117	1382263.046	329142.6
1989	1463101		4550070	1680835.125	336747.6
1990	1465166		4698743	1687975.219	344521.2
1991	1455061		4460547	1673579.499	352370.6
1992	1448460		4829691	1652224.65	360254.1
1993	1443127	2830813.3	4863760	1831934.421	368152.9
1994	1438973	2787721.237	5018868	1836056.927	376058.5
1995	1427974	2797124.06	4949627	1827204.142	383967.3
1996	1418946	2850067.461	4958414	1814158.494	391877.4
1997	1410631	2799034.691	5190341	1922253.931	399788.2
1998	1402980	2896911.307	5071963	1924558.345	407699.3
1999	1391478	2774651.862	5146852	1919045.169	415610.4
2000	1381085	2794509.994	5151927	1911005.8	423521.7
2001	1371093	2846196.11	5286403	1975953.725	431432.9
2002	1361474	2937763.268	5375874	1977162.742	439344.2
2003	1349690	3074577.474	5336641	1973661.674	447255.5
2004	1338529	3156682.078	5499459	1968638.58	455166.7
2005	1327594	3287526.848	5550803	2007590.204	463078
2006	1316868	3376330.859	5642415	2008139.246	470989.3
2007	1304925	3430265.209	5659390	2005850.47	478900.6
2008	1293332	3567469.328	5702324	2002644.676	486811.8
2009	1281866	3585418.719	5819492	2025933.573	494723.1
2010	1270519	3779665.03	5820120	2026084.981	502634.4
2011	1258486	3860095.861	5885045	2024526.609	510545.7
2012	1246650	3915037.114	5926743	2022415.735	518457
2013	1234886	3938039.461	6011491	2036267.867	526368.2
2014	1223188	3924805.514	6081267	2036179.702	534279.5
2015	1211105	3955385.988	6108225	2035061.397	542190.8
2016	1199133	3946932.689	6202402	2033610.21	550102.1
2017	1187201	3972147.914	6259494	2041776.707	558013.4
2018	1175306	4025288.658	6329982	2041544.199	565924.6
2019	1163195	4011742.447	6375639	2040691.033	573835.9
2020	1151146	4093701.903	6429933	2039637.307	581747.2
2021	1139119	4034473.204	6508923	2044378.219	589658.5
2022	1127114	4066394.126	6549142	2044058.745	597569.7
2023	1114986	4118728.489	6610752	2043365.326	605481
2024	1102894	4196641.262	6664634	2042551.069	613392.3
2025	1090815	4303574.03	6732839	2045228.071	621303.6
2026	1078747	4375417.828	6796062	2044856.2	629214.9
2027	1066611	4478521.992	6845041	2044259.028	637126.1
2028	1054494	4554662.573	6916382	2043589.051	645037.4
2029	1042385	4608438.88	6975386	2045022.552	652948.7
2030	1030282	4715621.726	7038846	2044619.112	660860
% change from 2012 to 2030	-17.35	20.44	18.76	1.09	27.12

further indicates that the methane emission is sustainable as it does not outweigh the agricultural output. But for the ANN-based results, the significant mean differences are observed for the OECD, upper middle-, and lower middle-income groups which further justify the sustainability of methane emission. The insignificant mean difference results for the middle-income and low-income groups may reveal unsustainable methane emission.

5. Discussion

As mentioned, we have attempted to make forecasting of methane emissions and agricultural value added by BJ and ANN methods and tested sustainability of such emissions vis-à-vis agricultural output for the major economic groups of the world for the time up to 2030. The results for methane emissions are seen to be declining for the OECD group but

Table 5: Forecasted values of agriculture output in current USD under the BJ method.

	OECD	Upper middle	Middle	Lower middle	Low
1981					
1982					
1983					28655746373
1984	77710044855.35				29759868468
1985	103315311309.63		474777328761	182501651690	31221206784
1986	124158617455.24	316887909136	492678373529	193724524521	33023207815
1987	131795851566.40	334580909413	517772413129	203354127983	35150085147
1988	97528609223.83	361108747377	538001902142	217447785160	37586783918
1989	68023008719.08	382302596062	564857171441	234100060898	40318946909
1990	139766033659.17	407106383042	597538283103	249778723353	43332882220
1991	182368403567.55	432417981365	626279435743	268185274811	46615532438
1992	217062773208.99	463657882375	660387025088	288155344067	50154445234
1993	172272259627.83	491318600145	699213155183	307530458795	53937745323
1994	235427769172.55	521401638240	734848183280	328572528916	57954107726
1995	334466976074.37	551825425022	774829664423	350570031761	62192732266
1996	334106517412.40	586227187857	818632846435	372203970453	66643319249
1997	316890720440.52	618227267450	859851450306	394856550400	71296046272
1998	346365067304.62	651852758691	904590389013	418092975119	76141546106
1999	383756726220.32	685706897185	952424648563	441107233457	81170885600
2000	399217028334.57	722230314612	998165573532	464743961966	86375545571
2001	410958400044.11	757142168169	1046757733111	488737465692	91747401615
2002	433001397999.27	793144696233	1097856894532	512595208232	97278705817
2003	456791256917.46	829300649879	1147260595639	536833329154	102962069301
2004	475742222179.18	867247727939	1198973605145	561289467882	108790445594
2005	493872649573.26	904113423550	1252717117643	585662645814	114757114761
2006	514276008566.72	941710977384	1305087421241	610268264947	120855668267
2007	535064791704.67	979411481982	1359328109431	635007110158	127079994554
2008	554785930372.17	1018313856727	1415213368572	659695259779	133424265273
2009	574326027095.09	1056490608353	1469986420799	684525449312	139882922163
2010	594367619206.43	1095158447334	1526274358835	709437050489	146450664536
2011	614494250582.09	1133895367753	1583894288807	734317672661	153122437337
2012	634385318873.25	1173438760262	1640613405931	759285092425	159893419766
2013	654236442407.45	1212495249261	1698559478743	784302261127	166759014418
2014	674198214948.72	1251881264912	1757584375498	809300499212	173714836936
2015	694178750394.64	1291313635198	1815879674392	834351777473	180756706132
2016	714107311641.00	1331287159814	1875168724927	859433456261	187880634578
2017	734027059550.69	1370933965196	1935331550347	884503566948	195082819625
2018	753971220850.90	1410801887684	1994903450537	909606089367	202359634838
2019	773919521963.40	1450700914796	2055280222764	934727188907	209707621832
2020	793856355585.46	1490963064218	2116364693922	959841219424	217123482486
2021	813791244649.35	1531005980352	2176970555359	984975056067	224604071515
2022	833731520238.19	1571197269233	2238228309050	1010120244795	232146389386
2023	853672709227.49	1611409429763	2300059251309	1035261113794	239747575567
2024	873611368051.09	1651865250565	2361502551863	1060414085898	247404902082
2025	893549597831.00	1692173962690	2423473841329	1085573995021	255115767372
2026	913489016083.73	1732582235055	2485909375009	1110731264449	262877690434
2027	933428635867.43	1773004512594	2548030944962	1135895929829	270688305235
2028	953367697400.09	1813590289668	2610580150446	1161064834276	278545355386
2029	973306664269.36	1854077354712	2673505362542	1186232125660	286446689058
2030	993245893361.05	1894631226103	2736176285121	1211403936555	294390254141
% change from 2012 to 2030	56.56	61.45	66.77	56.24	79.14

increasing for the remaining four groups. Referring to last row of Table 4 of the Appendix, the OECD group is expected to reduce the emission by 17.35 percent in 2030 in comparison to its value in 2012. The low-income group is expected to increase their emission levels by 27.12 percent, upper middle-income group by 20.44 percent, and middle income by 18.76 percent, and the lower middle-income group will face lowest emission of mere one percent. The predictions of OECDEO (2011) and USEIA (2016) are a little bit higher (30 percent) than that of the present study [24, 40].

Coming to the prediction of agricultural output, it is observed that all the groups have been showing increasing trends with the middle-income group at top of the list and the low-income group at the bottom with respect to the level values. Referring to Table 5 of the Appendix (last row), it is observed that the low-income group is expected to grow at

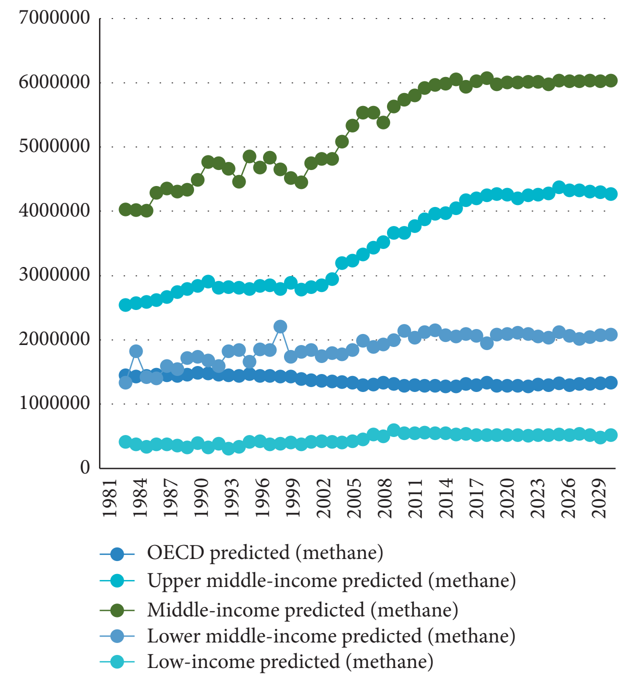

Figure 4: Forecasted methane emission by the ANN method. Source: sketched by the authors.

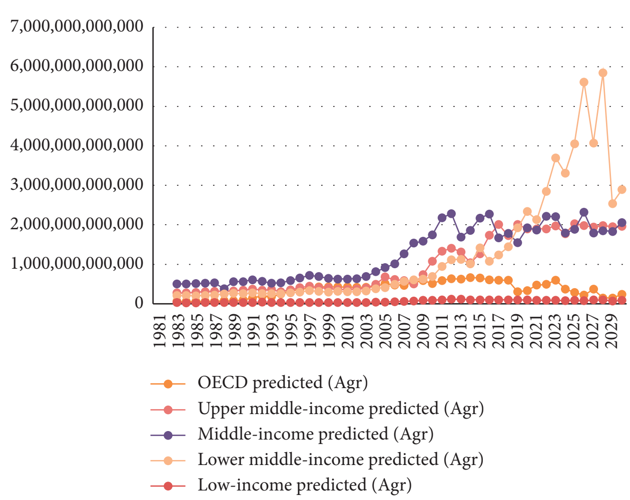

Figure 5: Forecasted agriculture output by the ANN method. Source: sketched by the authors.

the rate of 79 percent, middle group by 66.77 percent, upper middle by 61.45 percent, and OECD and lower middle group by 56.56 in 2030 with respect to 2012. All the results of forecasting are derived under the condition that all the associated indicators to methane emission will behave in the same manner in all the future period of prediction.

The sustainability of the methane emissions has been checked by the mean difference tests between the growth rates of the forecasted values of agricultural output and methane emissions. The results are positive and significant under the BJ method for all the groups which mean that the forecasted values of agriculture output are significantly

Table 6: Forecasted values of methane emission (in kt CO_2 equivalent) under the ANN method.

	OECD	Upper middle	Middle	Lower middle	Low
1981					
1982					
1983	1446416.968	2545150	4026870	1329748	412875
1984	1430021.447	2571500	4014406	1821735	372838
1985	1441795.832	2589046	4007588	1422605	335843
1986	1461538.199	2614282	4287438	1402827	369830
1987	1446995.651	2667094	4355718	1588817	373211
1988	1440210.728	2747220	4306775	1548814	352533
1989	1456140.5	2792646	4336595	1720628	331009
1990	1491361.472	2834851	4486574	1731676	389103
1991	1476079.287	2909815	4764961	1680329	325820
1992	1459493.477	2807767	4749263	1589611	384693
1993	1445983.108	2824382	4665474	1817914	307768
1994	1439778.73	2813669	4462412	1842438	339423
1995	1465050.103	2786787	4854905	1657465	415235
1996	1438339.671	2836269	4677620	1853525	420416
1997	1439059.021	2848776	4829725	1845757	375307
1998	1432454.551	2794881	4647779	2209993	384231
1999	1424597.677	2891541	4514477	1737921	400593
2000	1388451.979	2785951	4454832	1811381	371647
2001	1367643.85	2818457	4747838	1840412	410118
2002	1366140.269	2847352	4811888	1746807	418403
2003	1351195.076	2944943	4818147	1791565	411186
2004	1343380.827	3189900	5088023	1778178	399193
2005	1330945.301	3232285	5329671	1839492	422481
2006	1297305.527	3329724	5531115	1988915	454203
2007	1302505.141	3435593	5536095	1893808	529197
2008	1337349.195	3516933	5376779	1928591	501270
2009	1311392.359	3659730	5628762	1994891	598092
2010	1289029.284	3668891	5740748	2136971	549025
2011	1293807.527	3770809	5805986	2035394	551446
2012	1289158.193	3873620	5915579	2116978	554155
2013	1285810.736	3960180	5966076	2145107	542748
2014	1278758.189	3969299	5986994	2070499	545494
2015	1274290.358	4051914	6056242	2055028	530991
2016	1310605.759	4171557	5941071	2090889	541934
2017	1298863.228	4205484	6024229	2065535	518451
2018	1333476.5	4249025	6071401	1950702	516794
2019	1280933.927	4263922	5974434	2081918	517932
2020	1284397.121	4260086	6001380	2088591	515968
2021	1281190.139	4204223	6007384	2114227	515246
2022	1274927.663	4249874	6010389	2089217	511396
2023	1303026.248	4263496	6015199	2056467	514268
2024	1293290.107	4273741	5976227	2038449	519385
2025	1319416.3	4375672	6033272	2117189	526181
2026	1296397.731	4329229	6028447	2064709	522406
2027	1311785.835	4324037	6024229	2013127	540581
2028	1310999	4304192	6035686	2045801	519592
2029	1324572.071	4294304	6024831	2074644	481711
2030	1335745.338	4265628	6029050	2084001	514628

greater than that of methane emission. This further indicates that the methane emission is sustainable as it does not outweigh the agricultural output. But for the ANN-based results, the significant mean differences are observed for the OECD, upper middle-, and lower middle-income groups which further justify the sustainability of methane emission. Hence, it is recommended that, considering all the other

Table 7: Forecasted values of agriculture output in current USD under the ANN method.

	OECD	Upper middle	Middle	Lower middle	Low
1981					
1982					
1983	60149562148	275816000000	501816000000	208478000000	27914162124
1984	58623413411	273072000000	505240000000	208728000000	26378101124
1985	58512134674	289552000000	511902000000	205128000000	23808297707
1986	58687934646	305404000000	519899000000	211354000000	28931592469
1987	64737081234	317137000000	530667000000	220927000000	31653039004
1988	75454827282	317232000000	381891000000	245092000000	32486810073
1989	78636358047	325654000000	563200000000	264922000000	34863281281
1990	97586011959	345238000000	560167000000	255171000000	33617076366
1991	148770000000	374179000000	608340000000	274660000000	35340660729
1992	195534000000	345860000000	564271000000	258976000000	39010629608
1993	180284000000	360263000000	522557000000	259832000000	35238321276
1994	245800000000	309740000000	526438000000	253594000000	35270050041
1995	340404000000	356072000000	587710000000	272472000000	29869388592
1996	348603000000	408722000000	650495000000	296111000000	33179564625
1997	411922000000	446542000000	722873000000	329157000000	35083613270
1998	428733000000	405384000000	687618000000	318122000000	36849209370
1999	432306000000	398112000000	647510000000	292989000000	35432666001
2000	427107000000	357321000000	625239000000	317995000000	33687746404
2001	423704000000	363411000000	627118000000	304337000000	37074676523
2002	415854000000	368313000000	636532000000	307672000000	33399273994
2003	414608000000	398710000000	688031000000	327384000000	34299616147
2004	443383000000	496823000000	809029000000	384573000000	37145185371
2005	508433000000	677856000000	915925000000	409008000000	40513455887
2006	478442000000	612859000000	1014990000000	490946000000	54159541508
2007	468780000000	588534000000	1265260000000	569372000000	60077425963
2008	548197000000	501164000000	1534920000000	605306000000	70586165066
2009	586888000000	739111000000	1587530000000	625364000000	85904323805
2010	513235000000	1078720000000	1745390000000	687756000000	90543840883
2011	591661000000	1329470000000	2174670000000	947791000000	98291166756
2012	636341000000	1410410000000	2285030000000	1119160000000	113311000000
2013	623553000000	1316770000000	1689750000000	1125900000000	113776000000
2014	661119000000	1037670000000	1862420000000	1011140000000	100679000000
2015	655130000000	1266020000000	2170550000000	1416910000000	100257000000
2016	605669000000	1733390000000	2271590000000	1073130000000	100800000000
2017	600843000000	2007280000000	1667260000000	1238350000000	100759000000
2018	592490000000	1728370000000	1779174000000	1440630000000	100237000000
2019	303534000000	2006880000000	1550970000000	1921060000000	102262000000
2020	337184000000	1896250000000	1923180000000	2335620000000	93900354646
2021	472782000000	1897960000000	1868950000000	2128200000000	86932691913
2022	490161000000	1896060000000	2212620000000	2850170000000	92594909122
2023	599283000000	1974230000000	2208870000000	3696460000000	87350971903
2024	374703000000	1770710000000	1788500000000	3307450000000	80836950006
2025	290853369722	2030700000000	1883096000000	4048230000000	85262451407
2026	217660000000	1983130000000	2314470000000	5614650000000	78306777946
2027	367982000000	1941340000000	1789040000000	4069740000000	94908000000
2028	145581000000	1984130000000	1849430000000	5847880000000	96808438305
2029	147648000000	1948150000000	1833780000000	2539530000000	72947073894
2030	235620957663	1962620000000	2053360000000	2888470000000	88625925490

Table 8: Mean difference test results.

Groups	Mean difference under BJ method				Mean difference under ANN method			
	Mean (agri)	Mean (methane)	Corr. coefficient	t (agri−methane)	Mean (agri)	Mean (methane)	Corr. coefficient	t (agri−methane)
OECD	0.05539	−0.00813	**−0.98**	**2.70**	5.945	−0.1584	0.29	**1.74**
Upper middle	0.04064	0.01379	**0.97**	**7.40**	5.264	1.125	0.38	**1.85**
Middle	0.03892	0.0119	**0.99**	**17.06**	4.085	0.904	0.175	1.46
Lower middle	0.0420	0.0079	**0.78**	**24.12**	7.578	1.345	−0.003	**2.06**
Low	0.0495	0.0154	**0.99**	**28.94**	3.075	0.838	0.28	1.08

Note. Bold marks indicate significant results at 5% level. Source: authors' calculations.

factors of forecasting to be unchanged for the forecasting period, sustained agricultural activities may be a better solution which will be viable in economic as well as environmental fronts.

6. Conclusion

In our journey to forecast methane emission and agricultural output of world's leading groups by two methods, BJ and ANN, it is now to conclude the entire study. Both the methods of forecasting show that, except the OECD group, all the four remaining groups display increasing methane emission, but agricultural output is of increasing trends for all. Middle-income countries possess the top slot in both the methods. So, increase in methane emission is an alarming issue to the global leaders for the sake of environmental sustainability. Furthermore, testing for sustainability of such increasing emission vis-à-vis agricultural output, it is observed that the said emission is sustainable since the average growth rate of the latter is greater than that of the former. Hence, the environmental damage in true sense through methane emission may not be alarming as it boosts up the agricultural growth rate for all the groups. But the effect of methane emission upon other sectors of the economies for examining sustainability in a broader sense remains unverified. It may be kept as the agenda for future research.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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