Growing Green? Sectoral based prediction of GHG emission in Pakistan: A novel NDGM and Doubling time models Approach

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Abstract:

Greenhouse gases (GHGs) is one of the leading causes of global warming. Therefore, accuracy estimates for greenhouse gases (GHG) emissions are a key element in defining the best strategies for reducing GHG emissions from various source sectors of the economy. In the present study, an initial attempt has been made to estimate and forecast the GHG emissions in Pakistan from five major sectors, such as energy, industrial, agriculture, waste, land-use change, and forestry. The data was taken from the official website of the Pakistan climate database from 1990 to 2016. We employed advanced mathematical modeling, namely a non-homogenous discrete grey model (NDGM), to predict sector-wise GHGs emissions. Moreover, the present study is a milestone in the GHGs growth analysis by utilizing the Synthetic Relative Growth Rate (SRGR) and Synthetic Doubling Time model (SDTM). The results reveal that the industry, land-use change, and forestry contribute more in terms of increasing GHGs emissions till 2024, whereas agriculture and waste required comparatively less time to reduce GHGs emissions double in number among five sectors. All five sectors show an increasing trend in forecasting GHGs emissions between 1990 and 2016. However, the results indicate that land-use change, and forestry and industrial sector are more likely to be a reason for the increase in GHGs emissions in the future, followed by the agriculture, energy, and waste sector. The land-use change and forestry found prone to increase emission in the future, the doubling time (D_t) suggests less time expected to reduce GHGs. Finally, the study has suggested some policies for the policymakers, government, and decision-makers to reduce GHGs emissions and achieve sustainable development.

Keywords: Sustainable development; GHGs; emission; sectors; Pakistan; green

Highlights

- This study forecasts the GHG emissions in Pakistan from five major sectors such as energy, industrial, agriculture, waste, land-use change, and forestry.
- Industry, land-use change, and forestry contribute more in terms of increasing GHGs emissions until 2024
- This study has suggested some policies for the policymakers, government, and decision-makers to reduce GHGs emissions

1. Introduction

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Global climate change is an important issue faced globally by policymakers. The leading cause is the intensity of carbon dioxide (CO_2) and other gases (i.e. CH4, HFC, PFC, N2O, and SF6) emissions in the environment, as fossil fuels are being used since the industrialization of the eighteenth century and as a result of agricultural practices related to increase in the global population (Seinfeld & Pandis, 2006). The atmospheric carbon concentration was around 40% higher in 2011 than its pre-industrial level (Le Quéré et al., 2016). Moreover, global warming is a driving factor for climatic change, the United Nations Framework Convention Climate Change (UNFCCC) is struggling to ensure that the average global temperature does not rise beyond 2°C above the pre-industrial level so that uncontrollable adverse effects of climate change could be avoided. In this connection, the Kyoto Protocol was signed in 1997 and entered into force in 2005, with binding commitments on the emissions of greenhouse gas (GHG) by the industrialized countries (Grunewald & Martinez-Zarzoso, 2016). European Community and the thirty-seven industrialized nations committed themselves to the reduction of GHG emissions to an average of 5% over the 1990 level in the first commitment period (2008–2012). These goals were, however, not achieved successfully (Aichele & Felbermayr, 2013). The UNFCCC recently signed an international agreement, called the Paris Climate Agreement, at its 21st Conference of the Parties (COP-21), that promised to main global temperature under 2°C and attempted to restrict it 1.5°C (Schleussner et al., 2016). This is certainly a breakthrough and it is commendable that the agreement is ambitious but the work is yet to start (Rogelj et al., 2016).

A key element of UNFCCC's effort to stabilize GHG elevated levels and prevent unsustainable levels of anthropogenic global warming is to provide an organized record of countries ' GHG emissions so all their trends over time can be monitored adequately (Ikram et al., 2019). According to UNFCCC Article 4 and 12, all developing countries which primarily come in non-Annex I Parties are required to assemble and submit an inventory of national-level GHG emissions to the Parties Conference following the policy guidance set out in the Annex Decision 17 (Janerio, 1993).

Municipal solid waste (MSW) that produces a non-CO_2 GHG is considered to be the fourth major sector which contributes to global warming and climate change by emissions and adding around 5.5 to 6.4 percent to annual global emissions of methane 550Tg (Ngwabie et al., 2019; Zhang et al., 2019). Methane is generated by the excretion of organic substances either by dropping these municipal solids in landfills or handling and procedure of municipal sewage sludge (Qu et al., 2019; Tzemi and Breen, 2019). The landfills, which are the third major anthropological primary cause of methane emissions comes through agricultural activities and enteric fermentation (Chidet al., 2017; Rehman et., 2020). It accounts for 11 percent of the world's bio-gas emissions of methane in 50–55% by volume. It is expected that these emissions from landfills will increase by 816 Mt CO_2-eq by 2020. To make a significant contribution to this goal, the Government of Pakistan (GOP) has constructed and submitted its GHG emission inventory covering various socio-economic sectors for the year 1994 in compliance with the Intergovernmental Panel on Climate Change (IPCC) policies and send it to UNFCCC in 2003 together with its Initial National Communication (Distr, 2003; Sun et al., 2019).

In the current study, the GHG emissions which include CH4, CO2, and N2O are assessed based on the environmental activities in different sectors (land-use change and forestry (LUCF), industry, agriculture, waste, energy for the year 1990 to 2015 at the national level. All these GHG emission estimates are collectively presented as carbon dioxide CO_2 equivalents. As a result, the global warming potential (GWP) of N2O, CH_4, and CO_2 was taken as 310, 21, and 1 based on the duration of 100 years set out in the second assessment report of IPCC, following the underlined standards of Annex Decision 17 (Michaelowa & Michaelowa, 2015). The sectoral breakthrough of GHGs emission in Pakistan is presented in figure 1.

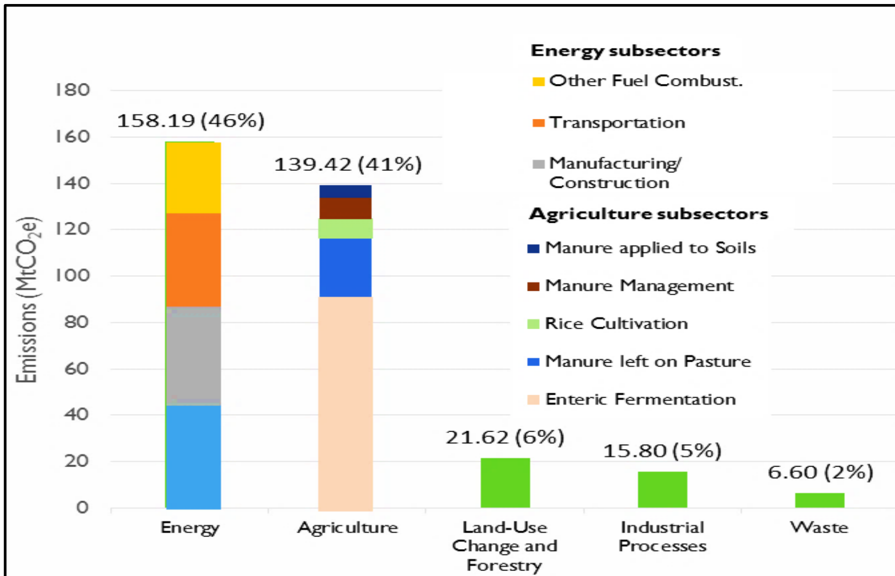

Figure 1: Sectoral breakthrough of GHG emission in Pakistan (*Sources: WRI CAIT 2.0, 2015; FAOSTAT)*

Pakistan is a sparsely populated country with over 199 million inhabitants in 2014, making it the sixth most populated country in the world (Pakistan Bureau of Statistics, 2014). According to the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) for the Asia region states that the susceptibility to climate change threats in agricultural-dependent economies i.e. Pakistan stems from their distinctive geography, demographic changes, socio-economic factors, and lack of adaptive potential, which together determine the vulnerability profile of perpetuation. Population growth and gross domestic product (GDP) have put considerable strain on natural resources while simultaneously increasing emissions of GHGs, air pollution, and health impacts (Baig & Baig, 2014; Uddin & Wadud, 2014; Climatelinks, 2019). The sectoral breakthrough of GHG emission of Pakistan is presented in Figure1. Ironically, none of Pakistan's cities has an effective and designed waste management system. The Pakistan Environmental Protection Act (PEPA) has been ineffectively applied and its rules do not seem to be a priority for solidified waste management. Inadequate waste management practices have adverse health and environmental effects and make the situation especially, in urban areas more complex.

This study aims to forecast the GHGs emission from 1990 to 2015 for five highly GHG emitted sectors which include Energy, Industrial sector, agriculture, waste, Land use change, and forestry by applying a non-homogenous discrete grey model (NDGM). The data used in this study was gathered from Pakistan's official climate database website for the period 1990 to 2015. Further, novel Synthetic Relative Growth Rate (RGR) and Synthetic Doubling Time (D_t) models were employed to undertake a comparative analysis of GHG emission relative growth rate among five sectors. Moreover, the MAPE% model was used to measure the level of accuracy for the proposed NDGM model. Finally, synthetic growth rate and synthetic doubling time models were employed to investigate the comparative analysis of five sectors in the long run regarding GHGs emissions. Hence, the present research is a pioneer study to forecast relative growth and required time to reduce the extent of GHG emission among five highly GHGs emitter sectors in Pakistan. Finally, the study proposed some suggestions for the government, policy, and decision-makers to take the appropriate measures to reduce GHGs emissions as well as to achieve sustainability.

The rest of the paper follows as: Section 2 provides the literature review of GHG emission in Pakistan; Section 3 presents the data collection and research method used for analysis. Section 4 explains the results and discussion. Finally, the conclusion and policy implication for the research are mentioned in section 5.

2. Literature Review

Many researchers carried out different studies for GHG emission sector-wise e.g. industry, agriculture, transportation, etc. (Khan and Siddiqui, 2017; Ren et al., 2014; Jiang et al., 2019). In this research, the emissions from GHG are evaluated as a result of the environment activities carried out at the national level between the year 1990 and 2015 in various sectors such as agriculture, waste, industrial processes, energy, land-use change, forestry (Tariq et al., 2017; Gocht et al., 2016; Khan et al., 2019). It has emerged that, due to the rapid increase in developing countries, such as China, India and Korea, and the subsequent energy needs, particularly clear energy, like natural gas, useful information has clearly been given to decision-makers in advance. Again, this triggers a massive surge in research on this topic. For example, (Zheng et al., 2020) predicted Chinese natural gas consumption from 2019 to 2023 on the basis of an optimized non-homogeneous grey model (ONGM (1, 1)). Similarly, (Gao et al., 2015) used four grey models to forecast projected Chinese Carbon emission from 2013 to 2015 and (Şahin, 2019) used a linear and non-linear rolling grey metabolic model based on optimization to forecast Turkey's GHG emissions, including land use, land use change and forestry (LULUCF), except LULU & the energy sector.

Since the industrial revolution in 1990, Pakistan's energy demands have been increasing exponentially every year. Over the last 19 years, primary energy consumption in Pakistan almost has risen to 67 Mtoe in 2013–2014 from an estimated 34 Mtoe of oil equivalent from 1994 to 1995 (Board et al., 2017). Although Pakistan is not predicted to play an important role in the anthropogenic climate change, the emissions from Pakistan are mainly based on the energy sector electricity, transport, and manufacturing, and one of the main sources contributing to air pollution and the GHG emissions (Purohit et al., 2019).

The energy sector is responsible for 46% of total Pakistani yearly GHG emissions, electricity consumption accounted for 26% of them, manufacturing for 25%, transportation for 23%, and other energy subsectors for 25% of the remaining emissions. Between 1990 and 2012, it expanded by 87 MtCO2e, which accounted for 55% of greenhouse gas emissions. In 2008, Pakistan had 147.8 million tons of CO2e equivalent emissions in total (Bakhshal Shah et al., 2018; Khan and Siddiqui, 2017). The subsectors of electricity and transport have been the big catalyst of a growing energy sector with 30% and 27% of the total energy sector growth, respectively (Z. Akram et al., 2019). In the electricity generation mix, the relative proportion of GHG-intensive fossil fuels (coal, oil, and natural gas) expanded from 54% in 1990 to 64% in 2012 (USAID, 2016). The overall energy usage has also increased during this period, growing 31 billion kWh in 1990 to 77 billion kWh, from 60% of the population in 1990 to 94% in 2012, driven by improved electricity access. The total consumption of fossil fuel in Pakistan's energy sector was 47.96 Mtoe in 2012. Out of this 14.19 and 13.26 Mtoe was used in the electricity generation sector and manufacturing sector, respectively. While 10.06, 1.24 and 6.46 Mtoe were for transportation, commercial/organization sector, and household sector respectively (Stiebert, 2016; Qureshi et al., 2016). Industrial process activity data are obtained from the Pakistan Economic Survey (Pakistan Bureau of Statistics, 2014). This comprises the production in Pakistan's chemical, mineral, and metal industries. While these mineral products include the processing of limestone paper, cement, ash, and dolomites, and the production of iron, urea, steel, and the chemical and metal industry provides ammonia. The total amount of soda ash, dolomite, and limestone were 0.17, 0.37, and 1.28 Tg respectively, while the amount of cement production was nearly 29.56 Tera grams (Tg) in 2012. Furthermore, the amount of urea produced by the chemical industry was 4.47 Tg, and the quantity of iron and steel produced by the metal industry was 0.25 Tg (Z. Akram et al., 2019).

For the agriculture sector in Pakistan, the activity data comprised of livestock population (i.e. mules, sheep, dairy and non-dairy cattle, buffalos, poultry, horses, asses, camels, goats, etc.) for assessing the emissions of methane from the domestic livestock manure management and enteric fermentation in 2012. In the same way, yearly data on crop production for sugarcane, paddy, and wheat have been collected to estimate the methane emissions from the burning of the residue of crops. Furthermore, 41% of total GHG emissions in the agriculture sector are mainly from enteric fermentation (46%). While the other 18 percent appeared from synthetic fertilizers and 14 percent of it happened to come from manure left on the pasture. Also, data are assimilated to quantify nitrogen intake from agricultural soil by application of synthesis fertilization, animal waste, and crop residues (Board et al., 2017; Akhmat et al., 2014).

The agriculture sector contributed 150 MtCO_2e GHG emissions in Pakistan in 2014, which represented 45.10% of its total emissions excluding land-use change and forestry (333 MtCO_2), and 41.53% including LUCF 362 MtCO_2. Most terrestrial biospheres have been converted into anthropic biomes by human populations and their land use. Around 4 percent of Pakistan's total land area covers forests, of which 5 percent is protected (Akhmat et al., 2014; Zaman, 2012; Bushra et al., 2018). This transition has resulted in the formation of a variety of new environmental trends and processes that has been influential for more than 8000 years (Canadell et al., 2007; Johnson et al., 2011; Colomb et al., 2014). Also, there are indirect impacts of other human activities on land cover, for example, forests and lakes that have been impacted by acid rain from the combustion of fossil fuel and Crops in the area of cities are affected by tropospheric ozone caused by toxic fumes of vehicles (Schleussner et al., 2016; Meyer, 1999). Moreover, these interventions in humans, largely caused by socio-economic considerations, often lead to changes in unbuilt and built-up land, given physical restrictions (P.-J. Liu et al., 2012). Changes in land use, which include land conversion from one kind to another and land cover alteration by land use management, have affected a significant proportion of the land surface of the earth. The aim is to meet the essential needs of human beings from natural resources (Turner et al., 2007; Franco Solís and De Miguel Vélez, 2018).

The changes worldwide to forests, agricultural land, rivers, and streams and air are caused by the fact that more than six billion people need food, water, fiber, and shelter. The last decade has seen the growth of global agricultural fields, plantations, urban areas, and pastures. This expansion is followed by significant growth in the consumption of energy, fertilizer, and water along with major biodiversity losses (Lambin et al., 2001; Zaks et al., 2009).

In Pakistan, nearly 20 Tg of solid waste are produced yearly, with a growth rate of approximately 2.4 percent annually (Fulton et al., 2017). This data consists of municipal solid waste which encompasses the yearly local solid waste disposal locations for the assessment of methane emissions produced from the land waste disposal (Khan and Ghouri, 2011; Kawai and Tasaki, 2016). Javed and Khan (2012), examined land usage/land cover changes activities between 2001 to 2010; they found that there has been a significant reduction of forested area, agricultural soil, and water resources, but mostly anthropogenic activities have expanded due to settlements, uncultivated land, and wastelands (Akram et al., 2018; Rothwell et al., 2016). Changes in land-use may influence each other. Many environmental impacts from land-use change represent collaborative effects as a result of a diverse change in land use. Deforestation, for instance, resulted in freshwater habitats being destroyed as rivers stilted. Likewise, as a carbon sink and source, the position of the Asian forest varies from year to year or from place to place because of its interconnected impacts between deforestation, reforestation, and afforestation. Consequently, the associations between the various land needs along their changing paths pose 53 obstacles to understand better the issue of land-use change and forestry. Land use and ecosystem changes and their impact on global climate change and sustainability are leading research concerns in environmental sciences for researchers and humans also (Lambin et al., 2001; Balbus et al., 2007; Turner et al., 2007).

In this study, we employed the Grey forecasting model namely NDGM to estimate the GHG emission in five major sectors of Pakistan. Also, this study is a milestone in the GHGs growth analysis by utilizing the Synthetic Relative Growth Rate (SRGR) and Synthetic Doubling Time model (SDTM) that will help to analyze the comparatively less time to reduce GHGs emissions double in number among five sectors.

3.1. Data

Pakistan's GHG emission dataset was abstracted from Pakistan's official climate website for the period 1990-2016. The five significant sectors i.e. the energy, agriculture, industrial, land-use change and forestry, and waste sectors of Pakistan, which are the main cause of GHGs emissions, have been selected for our research. Further, a Grey system software (version 8.0) was used to forecast the emission of GHGs for each sector from 2016 to 2024 by a non-homogeneous discrete grey model (NDGM). However, MS EXCEL and MATLAB were also utilized to solve NDGM. The current analysis and modeling methodology were used for the first time in the forecasting study to assess the sector's wise impact on GHG emissions. The structure of forecasting the GHG emission is operationalized in this study presented in Figure 2.

3.2Grey Forecasting Model

3.2.1. Nonhomogeneous discrete grey model (NDGM)

The NDGM system is designed based on non-homogenous exponential growth approximation law in order to comply with the assumptions of an actual data sequence. Xie et al., (2013) recommended that the real data sequence competes with a homogeneous pattern such as GM (1, 1). The accuracy of the NDGM model is significantly improved over the other grey models as far as the mean sequence value and the value of the intervals are concerned. NDGM model has been used in various disciplines, such as predicting Turkey's electricity consumption and analyzing the NDGM is the best fit and predicting more accurately than other grey predicting models. Ikram et al., (2020) predicted the future trend of ISO 9001 certification of by utilizing the NDGM model. Moreover, Duan et al., (2018) predicted the consumption of crude oil in China and analyzed that the NDGM showed superior performance.

In the model of NDGM, $x^{(0)}$ denotes the original data sequence and $x^{(1)}$ represents the accumulated sequence of data. So, we write it as follows:

$$\hat{x}^{(1)}(L+1) = \beta_1 \hat{x}^{(1)}(L) + \beta_2.\mathrm{L} + \beta_3 \tag{1}$$

$$\hat{x}^{(1)}(1) = x^{(1)}(1) + \beta_4 \tag{2}$$

$\hat{x}^{(1)}$(L), represents the predicted value $x^{(1)}$ along with their parameters β_1, β_2, β_3, and β_4. So, the above equation can be written in matrix form as below: where L=1, 2, and 3…. n-1

$$\begin{bmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ \vdots \\ x^{(1)}(n) \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} \begin{bmatrix} x^{(1)}(1) & 1 & 1 \\ x^{(1)}(2) & 2 & 1 \\ \vdots & \vdots & \vdots \\ x^{(1)}(n-1) & L-1 & 1 \end{bmatrix}$$

The input data in a single case indicates a constant sequence for the NDGM parameters β_1, β_2, β_3, and β_4, so by applying this relation in equation (3), we get it as:

$$\hat{\beta} = (B^{\mathrm{T}}B)^{-1}B^{\mathrm{T}}Y = [\beta_1, \beta_2, \beta_3]^{\mathrm{T}} \tag{3}$$

Whereas,

$$B = \begin{bmatrix} x^{(1)}(1) & 1 & 1 \\ x^{(1)}(2) & 2 & 1 \\ \vdots & \vdots & \vdots \\ x^{(1)}(n-1) & L-1 & 1 \end{bmatrix}, \quad Y = \begin{bmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ \vdots \\ x^{(1)}(n) \end{bmatrix},$$

Further, to calculate β_4 the following formula is being used where we minimize the sum of square error as:

$$\beta_4 = \frac{\sum_{L=1}^{n-1}\left[x^{(1)}(L+1)-\beta_1^L x^{(1)}(1)-\beta_2\sum_{j=1}^{L} j\beta_1^{L-j}-\frac{1-\beta_1^L}{1-\beta_1}.\beta_3\right].\beta_1^L}{1-\sum_{L=1}^{n-1}\left(\beta_1^L\right)^2} \tag{4}$$

$$\hat{x}^{(1)}(\mathrm{L}+1) = \beta_1^L \hat{x}^{(1)}(1) + \beta_2 \sum_{j=1}^{L} j\beta_1^{L-j} + \frac{1-\beta_1^L}{1-\beta_1}\cdot\beta_3; \quad L = 1,2,\ldots,n-1 \tag{5}$$

For the additional knowledge of the NDGM model, its parameter and properties, (Liu and Forrest 2010) is suggested (S. Liu et al., 2017).

3.2.2 Performance evaluation approach of NDGM

To assess the accuracy of the NDGM model, we used the MAPE. The formulae for mean absolute percentage error (MAPE) % computation is as follows:

$$\mathrm{MAPE}(\%) = \frac{1}{n}\sum_{L=1}^{n}\left|\frac{x^{(0)}(L)-\hat{x}^{(0)}(L)}{x^{(0)}(L)}\right|\times 100\% \tag{6}$$

Where $x^{(0)}(L)$ represents the actual values of the data. While $\hat{x}^{(0)}(L)$ denotes the forecasted data.

3.2.3 The growth of GHSs emissions and doubling time analysis

There is no model of GHG emissions available to monitor the rate of growth. RGR model was used in this way to analyze the sector's wise relative growth of GHG emissions. To reach this objective, the literature proposes the use of relative growth rate and doubling time models that have been used to analyze the ISO 14001 certification and research output growth over time (Ikram et al., 2019; Javed and Liu, 2018).

Using the NDGM method, two parameters (D_t and RGR) were used to forecast GHGs emissions in five major sectors of Pakistan. The RGR formula is given by,

$$\mathrm{RGR} = (\ln L_2 - \ln L_1)/(t_2 - t_1) \tag{7}$$

Where L_2 depicts cumulative GHG emissions in the year t_2 & L_1 signifies cumulative GHG emissions in the year t_1. In the analysis, as $t_2 - t_1$ is one year, equation (7) can be interpreted as equation (8).

$$\mathrm{RGR} = \ln(L_2/L_1) \tag{8}$$

And, doubling time (D_t) depicts the time required to reduce GHGs emissions double in numbers for specified RGR. So, the (D_t) is presented as:

$$D_\mathrm{t} = (t_2 - t_1)\ln[2/(\ln L_2 - \ln L_1)] \tag{9}$$

We can also rewrite this equation as follows:

$$D_\mathrm{t} = \ln[2/(\ln L_2 - \ln L_1)] \tag{10}$$

If the relative Growth rate (RGR) and doubling time (D_t) gives a different pattern for actual and simulated data, in any case, the synthetic Relative Growth Rate ($\mathrm{RGR_{syn}}$) and Synthetic Doubling Time ($\mathrm{D_{syn}}$) models have been introduced to jump into the conclusion for further accuracy. The Synthetic Relative Growth Rate ($\mathrm{RGR_{syn}}$) model is characterized in the following equation as:

$$\mathrm{D_{syn}} = \theta(\mathrm{D_a}) + (1-\theta)(D_\mathrm{f}) \tag{11}$$

Whereas $\mathrm{RGR_a}$ is a Relative Growth Rate of actual values of data. While $\mathrm{RGR_f}$ depicts forecasted values of the Relative Growth Rate. However, θ represents the relative weights coefficient and mostly it is considered to be 0.5.

The Synthetic Doubling Time ($\mathrm{D_{syn}}$) model is shown below in equation (12)

$$\mathrm{D_{syn}} = \theta(\mathrm{D_a}) + (1-\theta)(D_\mathrm{f}) \tag{12}$$

Where, $\mathrm{D_a}$ signifies the Doubling Time acquired from actual values, whereas $\mathrm{RGR_f}$ represents the Relative Growth Rate of forecasted values.

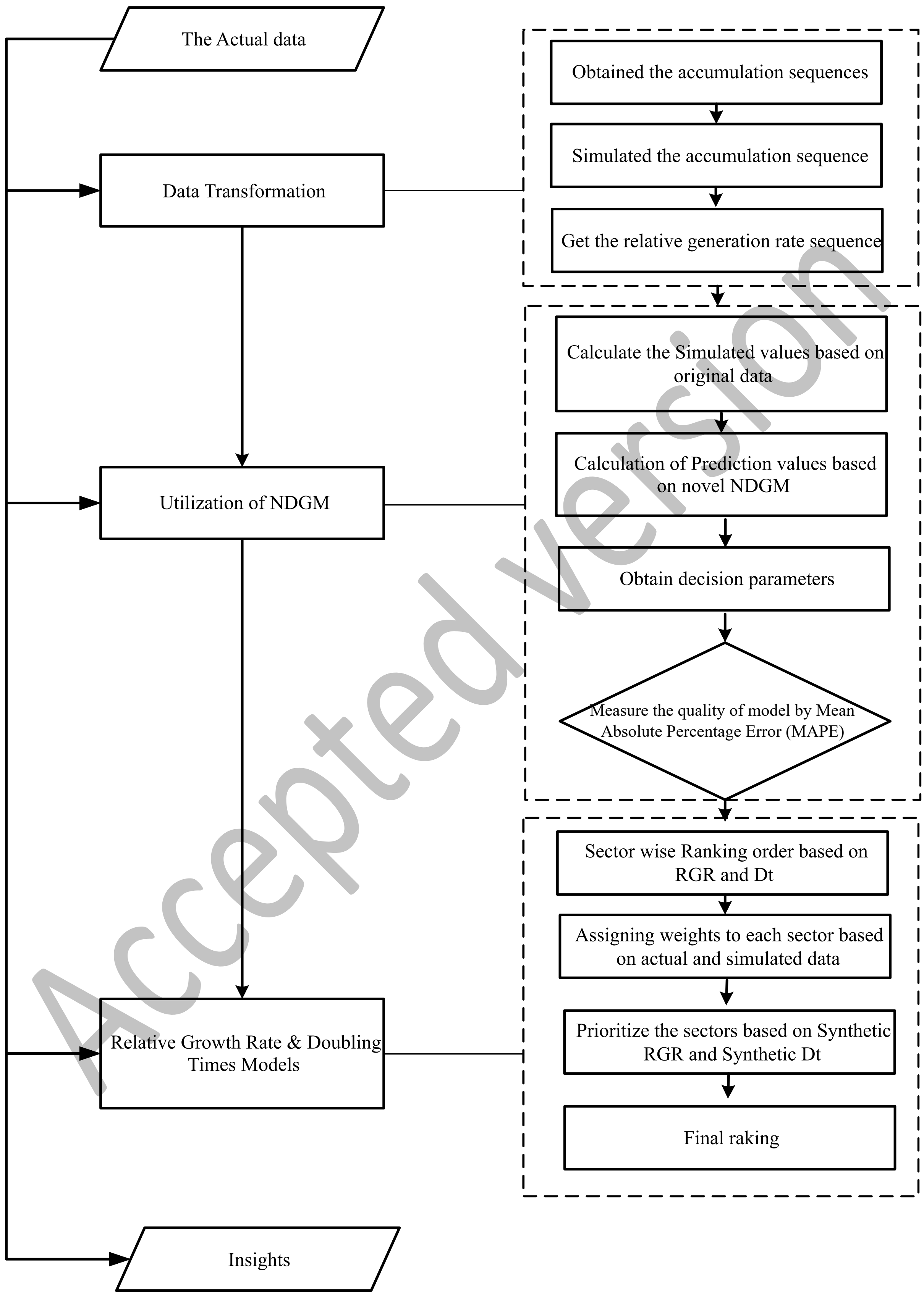
The Actual data
Data Transformation
Obtained the accumulation sequences
Simulated the accumulation sequence
Get the relative generation rate sequence
Utilization of NDGM
Calculate the Simulated values based on original data
Calculation of Prediction values based on novel NDGM
Obtain decision parameters
Measure the quality of model by Mean Absolute Percentage Error (MAPE)
Relative Growth Rate & Doubling Times Models
Sector wise Ranking order based on RGR and Dt
Assigning weights to each sector based on actual and simulated data
Prioritize the sectors based on Synthetic RGR and Synthetic Dt
Final raking
Insights

Figure 2: Structure of forecasting operationalized in this study

4. Results

We employed the NDGM model to forecast the GHGs emission in five different sectors of Pakistan i.e. Energy, agriculture, industrial sector, Land use change and forestry, and waste. The data utilized in this study is from 1990 to 2015. The simulated values calculated from the NDGM model for the GHG emission are given in Table 1, 2, 3, 4, and 5. The results for the energy sector of Pakistan are displayed in table 1. To check the accuracy of the proposed model, the Mean Percentage Absolute Error (MAPE) % has been utilized. The findings estimated through MAPE % show the level of effectiveness with the value 97.77% which demonstrates that the NDGM is a best-fit grey model to forecast the emission of GHGs.

For the case of energy sector GHGs emission in Pakistan, the parameters of NDGM are β_1= 0.967807, $\beta_{2=}$ 8005234.5, $\beta_{3=}$ 62010330.4 and $\beta_{4=}$ 86968.41. Additionally, the MAPE % for the energy sector of Pakistan is 97.42 % which shows the accuracy level of the model. To get a clearer view, the actual data and the simulated data estimated through NDGM from the year 1990 to 2024 against the total GHGs emission in quadrillions British units. According to simulated values of GHGs in energy sector computed by NDGM a inclined trend from 1990 to 2014 is recorded which started from 68.34 million (MtCO2e) to 163.60 million (MtCO2e). While the predicted values of energy sector in Pakistan from 2015 to 2024 are 166.25, 168.50, 171.50, 173.90, 176.30, 178.80, 180.50, 183.10, 185.70, and 187.10 million (MtCO2e) respectively.

Energy plays an important role in economic development and high consumption of energy has become a benchmark of living standard in the world. Whereas rapidly increase of energy consumption is positive indicator of economic growth; however, it also causes increase in emission of GHGs and climate vulnerability. In the past decade, energy sector has reported the high emitted sector of GHG in Pakistan and CO_2 emission are the most hazardous among others in GHGs due to consumption of fossil fuels (Ikram et al., 2020). Previous studies have investigated the effect of energy consumption on environment by using statistical models and reported that the energy sector is high contributor in emission of CO2 which make the climate vulnerable (Lin & Raza, 2019; Rehman et al., 2020). Similarly, another study conducted by (Sun et al., 2019) endorsed our finding that the energy sector contributed about 50% of the total GHG emission in Pakistan. To fulfill the energy demand of Pakistan the 99% of energy produced by conventional methods, whereas, less than 1% of energy demands is met by renewable methods (Kamran, 2018) .

Table 1: Forecasting the energy sector GHGs emission in Pakistan

Years	Energy	NDGM	Cumulative	RGR	Mean RGR	Dt	Mean Dt
1990	68335925.3	68335925.34	68335925.34				
1991	67873281.7	67812794.16	136209207	0.690	0.157	1.065	2.804
1992	74864784.7	73634899.2	211073991.7	0.438		1.519	
1993	81866287.7	79269570.44	292940279.3	0.328		1.809	
1994	84847790.7	84722842.05	377788070	0.254		2.062	
1995	91529293.7	90000553.89	469317363.7	0.217		2.221	
1996	96045113.7	95108357.86	565362477.4	0.186		2.374	
1997	99950933.8	100051723.9	665313411.2	0.163		2.508	
1998	101736754	104835945.8	767050165.1	0.142		2.643	
1999	110502574	109466146.9	877552739.1	0.135		2.699	
2000	110348394	113947285.8	987901133.2	0.118		2.826	
2001	112018946	118284161.3	1099920080	0.107		2.924	
2002	115039499	122481417.7	1214959578	0.099		3.001	
2003	118550051	126543549.8	1333509629	0.093		3.067	
2004	131510603	130474907.8	1465020231	0.094		3.057	
2005	134291155	134279701.7	1599311386	0.088		3.127	
2006	144311698	137962006.1	1743623084	0.086		3.142	
2007	156302240	141525764.3	1899925325	0.086		3.148	
2008	150982783	144974792.7	2050908108	0.076		3.264	
2009	154773326	148312784.9	2205681433	0.073		3.314	
2010	151203868	151543315.6	2356885302	0.066		3.407	
2011	152845089	154669844.3	2509730391	0.063		3.460	
2012	155000429	157695719.1	2664730820	0.060		3.508	
2013	156291650	160624180.5	2821022470	0.057		3.558	
2014	158962870	163458364.6	2979985340	0.055		3.597	
2015		166201306.5	166201306.5				
2016		168855943.5	335057249.9	0.701		1.048	
2017		171425118.5	506482368.4	0.413		1.577	
2018		173911582.9	680393951.3	0.295		1.913	
2019		176317999.3	856711950.6	0.230	0.263	2.161	2.211
2020		178646944.8	1035358895	0.189		2.357	
2021		180900913.5	1216259809	0.161		2.519	
2022		183082319.1	1399342128	0.140		2.658	

2023	185193497.7	1584535626	0.124	2.778
2024	187236710.1	1771772336	0.112	2.885

Table 2 depicts the findings from the industrial sector of Pakistan with the MAPE of 98.50% which shows the level of accuracy. The calculated parameters for the NDGM forecasting equation are given as: β_1= 1.057032, β_2= 223823.87, β_3= 2029683.7, and β_4= 283148.2.

In table 2, GHGs emissions of industrial sector have shown the increasing trend from 1990 to 2014 by utilizing the NDGM prediction model. The simulated values start 3.72 million (MtCO2e) and reached 196.63 million (MtCO2e). But original values of GHGs in the industrial sector are little different than simulated values which can be noted in the NDGM column of the table. Whereas the forecasted values for the industrial sector in Pakistan have been calculated for the year 2015 to 2024. These predicted values are elevating from 20.27 million (MtCO2e) and reached a level of 36.38 million (MtCO2e).

It has reported that, 59 billion bricks are annually produced by using various types of fuels such as coal, agriculture waste, plastic, rubber tires, rice husk and different types of industrial waste which are emitting hazardous and toxic gases and ultimately cause air pollution. Whereas, the Pakistan fertilizer demand has increased for last 30 years and production capacity has reached to 10 million metric tons yearly (69 % for Urea and 31% for DAP and potash), and natural gas is used as fuel for production of fertilizer. Moreover, the cement industry of Pakistan produced 4100 thousands of tons yearly and contributes considerably to Gross Domestic Production (GDP). The domestic and imported coal is the major fuel consumed in production of cement in Pakistan. According to World Steel Association (WSA), the total Pakistan's steel consumption in 2018 was recorded 4.7 million tones and ranked on 32 number globally (WSA, 2019). As per world bank statistics , in 2014 Pakistan contributed 23.84% CO_2 emissions from manufacturing industries and construction (% of total fuel combustion) (The World Bank, 2020).

Table 2: Forecasting the industrial sector GHGs emission in Pakistan

Years	Industry	NDGM	Cumulative	RGR	Mean RGR	Dt	Mean Dt
1990	3798821.7	3798821.72	3798821.72				
1991	3938114.9	2486309.25	7736936.64	0.711	0.170	1.034	2.638
1992	3956496.1	2851931.56	11693432.76	0.413		1.577	
1993	4224029.3	3238405.94	15917462.09	0.308		1.870	
1994	4117834.5	3646921.6	20035296.62	0.230		2.162	
1995	4363383.7	4078735.61	24398680.35	0.197		2.318	
1996	4549678.8	4535176.71	28948359.19	0.171		2.459	
1997	4633381.9	5017649.41	33581741.13	0.148		2.601	
1998	4618157	5527638.36	38199898.17	0.129		2.742	
1999	4998644.2	6066712.84	43198542.32	0.123		2.789	
2000	5177611.3	6636531.65	48376153.57	0.113		2.872	
2001	5817989.5	7238848.2	54194143.05	0.114		2.869	
2002	5908767.71	7875515.892	60102910.76	0.103		2.961	
2003	6996153.93	8548493.82	67099064.69	0.110		2.899	
2004	8083540.16	9259852.823	75182604.85	0.114		2.867	
2005	9170926.39	10011781.84	84353531.24	0.115		2.855	
2006	11059791.7	10806594.64	95413322.96	0.123		2.787	
2007	13663137	11646736.98	109076460	0.134		2.704	
2008	16251826.4	12534794.05	125328286.4	0.139		2.667	
2009	15869011.7	13473498.53	141197298.1	0.119		2.820	
2010	15988165	14465738.93	157185463.1	0.107		2.926	
2011	15578622.6	15514568.47	172764085.7	0.095		3.052	
2012	16165688.3	16623214.56	188929774	0.089		3.107	
2013	16752753.9	17795088.61	205682527.9	0.085		3.159	
2014	17339819.5	19033796.63	223022347.4	0.081		3.207	
2015		20343150.27	20343150.27				
2016		21727178.58	42070328.85	0.727		1.013	
2017		23190140.38	65260469.23	0.439		1.516	
2018		24736537.37	89997006.6	0.321		1.828	
2019		26371128.01	116368134.6	0.257	0.290	2.052	2.079
2020		28098942.14	144467076.7	0.216		2.224	
2021		29925296.44	174392373.2	0.188		2.363	
2022		31855810.83	206248184	0.168		2.478	
2023		33896425.74	240144609.7	0.152		2.576	
2024		36053420.38	276198030.1	0.140		2.660	

Table 3 shows the results of the Agriculture sector with 97.69% MAPE accuracy level and the calculated parameters for NDGM forecasting equations are β_1= 1.034794, β_2= -591865.01, β_3= 76086437.7, and β_4= 37308.19.

In the same way, identical results were derived by the NDGM model can be seen in table 4. Likewise, the agriculture sector is the major contributor in GDP and has considered the backbone of economy development. As the original data is starting from 77 million (MtCO2e) to 151 million (MtCO2e) from 1990 to 2014. Whereas simulated values and original values are approximately the same. The increasing trend has been observed from 1990 to 2014 while forecasted values have been calculated for the year 2015 to 2024 under the NDGM grey model which started about 156.1 million (MtCO2e) and reached the level of approximately to 206.6 million (MtCO2e).

A major part of Pakistan's economy relies on agriculture. 21% of GDP comes from agriculture and livestock, whereas 51% of the labor force and contributed to foreign reserve (Rehman et al., 2017). In the last few decades livestock industry has become major portion of agriculture sector due to high population growth rate, improving the living standard, and high food demand. Meanwhile, the emission level of GHGs in agriculture sector has risen simultaneously. Agriculture is primarily source of many developing countries' economies, the CO2 emission is increasing drastically due to low production of crop land, will ultimately negative affect on socio-economic development (Abas et al., 2017).

Table 3: Forecasting the agricultural sector GHGs emission in Pakistan

Years	Agriculture	NDGM	Cumulative	RGR	Mean RGR	Dt	Mean Dt
1990	77097486	77097486	77097486				
1991	78236535	78178362.7	155334021.3	0.701	0.149	1.049	2.869
1992	80371503	80306597.16	235705524.6	0.417		1.568	
1993	82680670	82508880.36	318386194.6	0.301		1.895	
1994	84416060	84787788.72	402802254.7	0.235		2.141	
1995	87871568	87145988.29	490673823.1	0.197		2.316	

1996	90620650	89586237.9	581294472.8	0.169		2.468	
1997	93126814	92111392.35	674421286.9	0.149		2.600	
1998	95110789	94724405.78	769532076.2	0.132		2.719	
1999	98121172	97428335.12	867653248.2	0.120		2.813	
2000	99801592	100226343.6	967454840	0.109		2.911	
2001	1.01E+08	103121704.7	1068268041	0.099		3.005	
2002	1.04E+08	106117805.5	1172034975	0.093		3.072	
2003	1.07E+08	109218151.2	1279223986	0.088		3.129	
2004	1.1E+08	112426368.8	1389442187	0.083		3.186	
2005	1.15E+08	115746211.5	1503952328	0.079		3.229	
2006	1.21E+08	119181563.2	1625350477	0.078		3.249	
2007	1.23E+08	122736442.8	1748596109	0.073		3.309	
2008	1.29E+08	126415009.2	1877530752	0.071		3.336	
2009	1.35E+08	130221565.8	2012899317	0.070		3.358	
2010	1.34E+08	134160565.8	2146416164	0.064		3.439	
2011	1.39E+08	138236617.5	2285551568	0.063		3.461	
2012	1.39E+08	142454489.3	2424926742	0.059		3.520	
2013	1.47E+08	146819115.6	2571985082	0.059		3.525	
2014	1.5E+08	151335602.7	2722325853	0.057		3.561	
2015		156009234.1	156009234.1				
2016		160845477.6	316854711.7	0.709		1.038	
2017		165849991	482704702.7	0.421		1.558	
2018		171028628.9	653733331.6	0.303		1.886	
2019		176387449.8	830120781.4	0.239	0.272	2.125	2.164
2020		181932722.9	1012053504	0.198		2.312	
2021		187670935.5	1199724440	0.170		2.464	
2022		193608800.6	1393333240	0.150		2.593	
2023		199753264.9	1593086505	0.134		2.703	
2024		206111516.6	1799198022	0.122		2.800	

Likewise, table 4 represents the findings for waste sector of Pakistan with the MAPE accuracy level of 96.60%. The estimated parameters of the NDGM forecasting equation for the case of waste sector GHGs emission are β_1= 0.987673, β_2= 148443.18, β_3= 4899681.79and β_4= 18648.22.

On the other hand, the waste sector is producing comparatively lower GHG emission than energy, industrial and waste sectors. The simulated values are starting from 4 million (MtCO2e) and leveled up to 6 million (MtCO2e) under NDGM. Table 4 presents the uprising trend of GHGs in agriculture sector from 1990 to 2024. While the predicting values of agriculture sector in Pakistan from 2015 to 2024 are 6803666, 6868239, 6932016, 7057220, 7179357, 7179357, 7239299, 7298502, and 7356975 (MtCO2e) respectively.

Solid waste management is a crucial issue and threat for environmental sustainability in Pakistan. Pakistan produces 20 million tons of solid waste annually, which has been drastically increasing 2% every year. The major metropolitan area of Pakistan is producing 71000 tons of solid waste per day (United Nations, 2018). The waste sector is producing comparatively low GHGs compared to energy and industrial sectors. The cumulative emission of GHGs in 2015 from waste sector is recorded 417.84 (Gg CO_2 equivalent), which comprises on Methane 237.51, Carbon dioxide 0.53 and Nitroxide 179.8 (Gg CO_2 equivalent) respectively (Ilmas et al., 2018)**Table 4: Forecasting the waste GHGs emission in Pakistan**

Years	waste	NDGM	Cumulative	RGR	Mean RGR	Dt	Mean Dt
1990	4932198.4	4932198	4932198.36				
1991	5007346.8	4987324	9939545.16	0.70	0.14	1.05	2.96
1992	5082495.2	5074288	15022040.4	0.41		1.58	
1993	5157643.7	5160179	20179684.09	0.30		1.91	
1994	5232792.1	5245012	25412476.22	0.23		2.16	
1995	5307940.6	5328798	30720416.79	0.19		2.36	
1996	5395681.3	5411552	36116098.12	0.16		2.51	
1997	5483422.1	5493286	41599520.21	0.14		2.65	
1998	5571162.9	5574012	47170683.06	0.13		2.77	
1999	5658903.6	5653743	52829586.67	0.11		2.87	
2000	5746644.4	5732492	58576231.04	0.10		2.96	
2001	5820334.4	5810269	64396565.42	0.09		3.05	
2002	5894024.4	5887088	70290589.82	0.09		3.13	
2003	5967714.41	5962959	76258304.23	0.08		3.20	
2004	6041404.43	6037896	82299708.66	0.08		3.27	
2005	6115094.44	6111909	88414803.1	0.07		3.33	
2006	6185422.97	6185009	94600226.07	0.07		3.39	
2007	6255751.5	6257208	100855977.6	0.06		3.44	
2008	6326080.02	6328517	107182057.6	0.06		3.49	
2009	6396408.54	6398947	113578466.1	0.06		3.54	
2010	6466737.07	6468509	120045203.2	0.06		3.59	
2011	6534907.44	6537214	126580110.6	0.05		3.63	
2012	6603077.81	6605071	133183188.5	0.05		3.67	
2013	6671248.19	6672092	139854436.6	0.05		3.71	
2014	6739418.56	6738287	146593855.2	0.05		3.75	
2015		6803666	6803665.845				
2016		6868239	13671904.56	0.70		1.05	
2017		6932016	20603920.15	0.41		1.58	
2018		6995006	27598926.41	0.29		1.92	
2019		7057220	34656146.85	0.23		2.17	
2020		7118668	41774814.54	0.19	0.26	2.37	2.22
2021		7179357	48954172	0.16		2.53	
2022		7239299	56193471.1	0.14		2.67	
2023		7298502	63491972.93	0.12		2.80	
2024		7356975	70848947.67	0.11		2.90	

Table 5: Forecasting the land-use change and forestry GHGs emission in Pakistan

Years	LUCF	NDGM	Cumulative	RGR	Mean RGR	Dt	Mean Dt

1990	21635333.3	21635333	21635333.3				
1991	21635333.3	20941783	42577116.7	0.68	0.14	1.08	2.99
1992	21635333.3	20948998	63526114.63	0.40		1.61	
1993	21635333.3	20958299	84484413.33	0.29		1.95	
1994	21635333.3	20970289	105454702.3	0.22		2.20	
1995	21635333.3	20985747	126440448.9	0.18		2.40	
1996	21635333.3	21005674	147446123	0.15		2.57	
1997	21633333.3	21031364	168477487	0.13		2.71	
1998	21639333.3	21064483	189541969.9	0.12		2.83	
1999	21637333.3	21107179	210649148.5	0.11		2.94	
2000	21637333.3	21162221	231811369.5	0.10		3.04	
2001	20533333.3	21233180	253044549.5	0.09		3.13	
2002	20535333.3	21324658	274369207.9	0.08		3.21	
2003	20533333.3	21442590	295811797.8	0.08		3.28	
2004	20535333.3	21594624	317406421.7	0.07		3.35	
2005	20539333.3	21790622	339197043.7	0.07		3.41	
2006	22005000	22043297	361240341	0.06		3.46	
2007	22002000	22369039	383609380.4	0.06		3.51	
2008	22000000	22788977	406398357.6	0.06		3.55	
2009	22000000	23330349	429728707.1	0.06		3.58	
2010	22001000	24028272	453756978.8	0.05		3.60	
2011	28600000	24928014	478684992.7	0.05		3.62	
2012	28604000	26087937	504772929.5	0.05		3.63	
2013	28600000	27583278	532356207.1	0.05		3.63	
2014	28601000	29511030	561867236.9	0.05		3.61	
2015		31996235	31996235.1				
2016		35200093	67196328.58	0.74		0.99	
2017		39330420	106526748.3	0.46		1.47	
2018		44655123	151181871.1	0.35		1.74	
2019		51519584	202701455	0.29	0.34	1.92	1.87
2020		60369059	263070513.6	0.26		2.04	
2021		71777558	334848071.8	0.24		2.12	
2022		86485083	421333154.6	0.23		2.16	
2023		105000000	526778774	0.22		2.19	
2024		130000000	656667796.6	0.22		2.21	

While in the case of the land-use change and Forestry sector of Pakistan, the calculated values through the NDGM model are β_1=1.289173, β_2= 6048574.1, β_3= 20138514.6 and β_4= 20593.2. In table 5, GHGs emissions of land use change and forestry sector have shown the increasing trend from 1990 to 2014 by utilizing the NDGM prediction model. The simulated values start 21 million (MtCO2e) and reached 29 million (MtCO2e). The original values of GHGs in the industrial sector are same than simulated values which can be noted in the NDGM column of the table. Whereas the forecasted values for the land use change and forestry sector in Pakistan have been calculated for the year 2015 to 2024. These predicted values are elevating from 31 million (MtCO2e) and reached a level of 130 million (MtCO2e).

According to World Wildlife Fund (WWF), Pakistan is the second in Asia in term of deforestation. Due to human activities and land cover alteration many environmental issues are arising at the local and global level. Land use is contributing 30% of GHG emission, whereas about half of GHG emission emitted by deforestation (Szulczyk et al., 2020). The level of GHGs emission in Pakistan has increased up to 3% due to deforestation from 5% to 2.5% (United Nation Climate Change, 2019).

We employed the NDGM model to forecast GHGs emissions in five major sectors of Pakistan. The findings reveal that the MAPE accuracy level for the industrial sector is slightly higher than the other sectors of Pakistan when calculated through the NDGM. While the average MAPE accuracy level for the NDGM was recorded 97.77% and presented in table 6.

Table 6: MAPE % for different sectors of Pakistan

Sectors	MAPE % NDGM
Energy	2.85
Industrial Processes	1.50
Agriculture	2.31
Waste	3.40
Land-Use Change and Forestry	1.10
Average MAPE %	2.232
Overall accuracy Leve	97.768

Further, Table 7 demonstrates the ranking order of the Pakistan sector wise for the RGR and the doubling time (D_t) based on the actual and predicted dataset. The RGR equation for actual data presents a ranking order given below:

Industry $_{(0.170)}$> Energy $_{(0.157)}$>Agriculture $_{(0.149)}$>Waste $_{(0.140)}$>Land $_{(0.130)}$

When we calculated the required time for the reduction of GHGs emission in Pakistan sector-wise based on the original data set, the following sequence was observed as per doubling time (D_t) model:

Land $_{(2.990)}$> Waste $_{(2.960)}$>Agriculture $_{(2.869)}$>Industry $_{(2.638)}$>Energy $_{(2.080)}$

The outcomes as mentioned above illustrate that the RGR of GHGs emissions in the industrial and energy sector is relatively higher than agriculture, waste, land-use change, and forestry sector based on actual data set. However, these findings also show that the agricultural, industrial and energy sector requires additional time and efforts to reduce the emission of GHGs for a given RGR compared to Pakistan's waste, land use power and forestry sector.

Table 7: Ranking of RGR and doubling time for each sector

Relative Growth rate / Double Time	Ranking
RGR (Actual data)	Industry $_{(0.170)}$> Energy $_{(0.157)}$>Agriculture $_{(0.149)}$>Waste $_{(0.140)}$>Land $_{(0.130)}$
D_t (Actual Data)	Land $_{(2.990)}$> Waste $_{(2.960)}$>Agriculture $_{(2.869)}$>Industry $_{(2.638)}$>Energy $_{(2.080)}$
RGD (Simulated Data)	Land $_{(0.329)}$> Industry $_{(0.275)}$> Agriculture $_{(0.268)}$> Energy $_{(0.267)}$>Waste $_{(0.266)}$
D_t (Simulated data)	Waste $_{(2.220)}$> Energy $_{(2.211)}$> agriculture $_{(2.164)}$> Industry $_{(2.079)}$> Land $_{(1.870)}$

Moreover, we used simulated data based on NDGM to assess the 2016-2024 GHG emission in Pakistan. The following results are obtained, as shown by the RGR sequence:

Land $_{(0.329)}$> Industry $_{(0.275)}$> Agriculture $_{(0.268)}$> Energy $_{(0.267)}$> Waste $_{(0.266)}$

A different pattern is observed based on simulated results. For the period 2016-2024, land-use change and the industrial sector may endure progressive GHGs emissions in the form of the relative growth rate of 3.29% and 2.75% respectively follows by the agriculture, wastes, and energy sector.

Whereas doubling time (D_t) model also utilized based on simulated values sector-wise regarding GHGs emission comparison, the following pattern of results is obtained:

Waste $_{(2.220)}$> Energy $_{(2.211)}$> agriculture $_{(2.164)}$> Industry $_{(2.079)}$> Land $_{(1.870)}$

Our findings also reveal that Land-use change and industry 0.329 and 0.275 years respectively to double reduce GHGs emissions because of the higher RGR followed by the waste, energy, and agriculture sector.

By using the NDGM based on the original and simulated data, we make a prediction of the GHGs emission for the period from 2016 to 2024.

Presently a query arises here eventually as which country may endure maximum GHGs emissions in the long run. Therefore, to respond to this query, synthetic indices by original and forecasting values were employed, which suggests that RGR_{synth} the synthetic relative growth rate has been obtained as:

$$RGR_{synth} = (RGR_a) + (1- \Theta)\ (RGR_f)$$

Where RGR_a shows the relative growth derived from the original data sequence whereas, RGR_f shows the relative growth derived from the original data sequence. The value of Θ is taken as 0.5. Further, D_{synth} expresses synthetic doubling time (SDT) is as follows:

$$D_{synth} = \Theta\ (D_a) + (1- \Theta)\ (D_f)$$

Where D_a exhibits the time required double in number to reduce GHGs emissions based on original data, whereas, D_f present the time required double in number to reduce GHGs emissions based on forecasting values is presented in Table 8.

Land $_{(0.235)}$ > Industry $_{(0.230)}$ > agriculture $_{(0.211)}$> Energy $_{(0.210)}$ > Waste $_{(0.200)}$

As per doubling time D_t comparison based on SDT sector-wise, we contained a sequence as follows:

Waste $_{(2.590)}$ > Agriculture $_{(2.570)}$ > Land $_{(2.430)}$> Industry $_{(2.359)}$ > Energy $_{(2.146)}$

According to SRGR and SDT, we got different rankings, which differs from the ranking sequence by RGR and doubling time (D_t) of actual data. RGR synthetic and D synthetic sequence show through land-use change and the industrial sector may endure progressive GHGs emissions can be seen in Figure 3. The RGR of land-use change sector was recorded higher 0.235 among all five sectors, followed by Industrial sector 0.230, agriculture sector 0.211, energy sector 0.210 and waste sector 0.200 respectively. However, the waste and agricultural sector require more time to reduce double in numbers the GHGs emission as compared to the industrial sector in Pakistan. On the contrary, the energy sector requires relatively more time to reduce GHGs emissions as compared to other sectors.

Table 8: Ranking w.r.t synthetic RGR and Doubling Time model

Synthetic Relative Growth rate / Synthetic Double Time models	**Ranking**
RGR (Actual data)	Land $_{(0.235)}$ > Industry $_{(0.230)}$ > agriculture $_{(0.211)}$> Energy $_{(0.210)}$ > Waste $_{(0.200)}$
D_t (Actual Data)	Waste $_{(2.590)}$ > Agriculture $_{(2.570)}$ > Land $_{(2.430)}$> Industry $_{(2.359)}$ > Energy $_{(2.146)}$

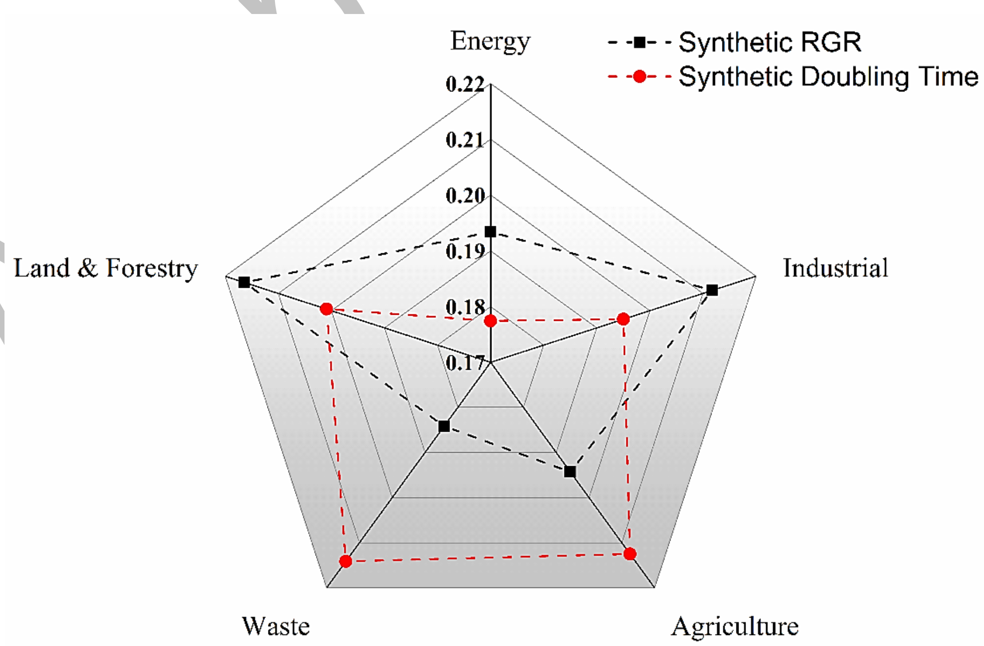

Figure 3: Synthetic RGR and Doubling time-based ranking of GHG of five sectors of Pakistan

5. Conclusion

In this study, we attempted to assess the growth and analyzed the future trends of GHGs emissions in Pakistan of five high emitting major sectors such as agriculture, industry, energy, land-use change, and forestry, and waste. To achieve this this objective, we used the GHGs emission data from 1990 to 2016. We take this process a step further and applied novel NDGM forecasting model to forecast the future trends of GHGs in Pakistan. Furthermore, we forecasted the GHG emissions until 2024 in all these sectors through NDGM and concluded that we have achieved the 97.77 % overall accuracy of NDGM model.. Further, we used synthetic RGR and conducted synthetic doubling time analysis which identified that the industrial sector and land-use change and forestry are major contributors to GHG emissions while the agriculture and waste sectors GHG emission reduction could be double in numbers as compared to industry, energy, land-use change and forestry sectors. All the five sectors showed the uprising trend of GHGs emission till 2024. The energy, waste and agriculture sectors showed the higher growth rate of emissions among others, which implies that the energy, agriculture and waste sector required more serious attentions to mitigate the GHGs emission. Moreover, industrial and land-use change, and forestry sectors are also contributing but comparatively less to country GHGs emission and will rise to 36053420.38 and 206111516.6 (MtCO2e) till 2024, respectively. The synthetic doubling time models showed that the waste and agriculture sectors required 2.590 and 2.570 time to decrease their GHGs emission double in number.

This means that if GHG emissions rise with the same pattern, it will be a serious threat in the future. To minimize and control air pollution, the government needs to take serious steps in order to mitigate the GHGs. In addition to identifying development areas or regions for GHGs, the government should also examine the types of GHG contaminants in these areas. New regulations and tracking networks must be established to reduce emissions as they function effectively. The Government should start awareness programs and promotions may change the public's minds towards waste management by various means (e.g. print media, digital media, and social media). Besides, the new industry should begin by taking mitigation objectives into account and make the environment more sustainable.

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

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