Prediction of Surface Temperature and CO₂ Emission using a novel grey system model

Pawan Kumar Singh

Thapar University: Thapar Institute of Engineering and Technology

Alok Kumar Pandey (✉ alokpandey@bhu.ac.in)

Banaras Hindu University <https://orcid.org/0000-0001-5604-3243>

Anushka Chouhan

Banaras Hindu University

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Abstract

The increase in surface temperature and CO₂ emissions are two of the most important issues in climate studies and global warming. The 'Global Emissions 2021' report identifies the six biggest contributors to CO₂ emissions; China, USA, India, Russia, Japan, and Germany. The current study projects the increase in surface temperature and the CO₂ emissions of these six countries by 2028. The EGM (1,1,α,θ) grey model is an even form of the model with a first order differential equation, that has one variable and a weightage background value that contains conformable fractional accumulation. The results show that while the CO₂ emissions for Japan, Germany, USA and Russia show a downward projection, they are expected to increase in India and remain nearly constant in China by 2028. The surface temperature has been projected to increase at a significant rate in all these countries. By comparing with the EGM (1,1) grey model, the results show that the EGM (1,1, α, θ) model performs better in both in-sample and out-of-sample forecasting. The paper also puts forward some policy suggestions to mitigate, manage and reduce increases in surface temperature as well as CO₂ emissions.

Introduction

Environment and climatic conditions affect human life; with global warming drawing the attention of scientists and researchers to the rising atmospheric temperature. Global warming negatively impacts human lives in terms of rising sea levels and the increasing number of extreme events (Melillo et al., 2014); while air temperature directly affects the land surface (Tajfar, Bateni, Lakshmi, et al., 2020), (Valipour et al., 2020) (Tajfar, Bateni, Margulis, et al., 2020). Health issues emerge due to variations in temperature (Lan et al., 2010), (Schulte et al., 2016), which also causes flora and fauna loss. An appropriate approach for air temperature prediction may help reduce the consequences of climate change and global warming. It can also play a vital role in framing policy for various business activities and energy-related matters. Nowadays, extreme weather is a common phenomenon that is being more frequently observed. Therefore, it is necessary to understand the changes in the weather condition. Temperature plays an important role in weather forecasting. Temperature prediction ability is useful for various activities performed in the future that determine economic abilities and ecological phenomenon (Sharma et al., 2011), (Sardans et al., 2006). Under climate change, temperature forecasting is an important research area. It is useful in understanding the macroscopic evolutionary processes, and also provides a significant reference source for sustainable economic development (H. Wang et al., 2019). Akram & El (2016) show that the LSTM based neural networks perform better in temperature prediction. H. Wang et al. (2019) used VMD-ARIMA model, ARIMA model, and Grey Model (1, 1) and found that VMD-ARIMA provides more accurate forecasts. Kärner (2009) advocate an intensive study for the short-term changes in different climate zones and total solar irradiance at the topmost of the atmosphere and surface air temperature series. Studies have been performed using ARIMA and its similar methods to predict weather conditions. Prybutok et al. (2000) created a neural network model for daily maximum ozone levels forecasting and compared it with the regression and Box-Jenkins ARIMA, concluding that the neural network model estimates better than regression and Box-Jenkins ARIMA models. Curceac et al. (2019) used non-parametric and parametric techniques for hourly air temperature forecast up to 24 hours in advance. The results suggest that Seasonal Autoregressive Moving Average (SARMA) performs better during the first six projected hours. Pooling projections improve forecasting accuracy. Nowadays, machine learning methods are becoming quite popular in weather forecasting. Machine learning techniques may be useful in improving regional air temperature forecasts in mid and high latitude regions where model capabilities are limited (Y. Feng et al., 2019) (Qian et al., 2020) (Ratnam et al., 2019) (Peng et al., 2020) (Cifuentes et al., 2020). Qian et al. (2020) used SVR and XGBoost in seasonal forecasts of the surface air temperature in winter in North America. The hindcasts of the SVR and XGBoost models outperform the L.R. model in terms of forecasting. The L.R. model is less affected by the size of the training data set. The genetic algorithm approach improves the spatial distribution of air temperature anomalies, resulting in a better representation of anomalies in predictions (Ratnam et al., 2019). Y. Feng et al. (2019) used four machine learning and empirical models for the daily global solar radiation prediction of temperate in China. The artificial neural network model and hybrid mind evolutionary algorithm give better estimates. Two machine learning methods of neural networks and natural gradient boosting (NGBoost) were used by Peng et al. (2020) to improve the prediction skills of the 2-m maximum air temperature with lead times of 1–35 days over East Asia. Post-processing approaches may effectively reduce prediction biases and uncertainties in the first two weeks during the validation phase. Neural networks and NGBoost perform as the best models in more than 90% of the study area (Peng et al., 2020). Cifuentes et al. (2020) disclose that Deep Learning approaches show smaller errors than traditional Artificial Neural Networks architectures. Appelhans et al. (2015) examined and compared a widely used kriging approach using a network of temperature monitoring plots throughout the southern slopes of Mt. Kilimanjaro. The ANN model has strong prediction performance as well as low computational and architectural complexities (Codeluppi et al., 2021). Jallal et al. (2019) suggest that an advanced autoregressive model, which has two hidden layers and a small number of hidden neurons, can effectively predict the target. Sanikhani et al. (2018) describe the development and application of data-intelligent models for air temperature estimation without climate-based inputs, using only geographic factors in a large spatial region in central India. The GRNN model is a qualified data-intelligent tool for temperature estimation without the need for climate-based inputs. This model can be investigated for its utility in energy management, building and construction, agriculture, heatwave studies, health, and other socio-economic areas, particularly forestry. LSTM and Facebook Prophet have been used to simulate the forecast of five-year daily air temperatures in Bandung. The results reveal that Prophet outperforms LSTM on maximum air temperature (Toharudin et al., 2021).

Researchers have studied the accuracy of several grey models, such as G.M. (1,1), Grey Verhulst model, and modified grey models (Kayacan et al., 2010) (Guo et al., 2011) (X. Wang et al., 2014) (Hamzacebi & Es, 2014) (S. J. Feng et al., 2012) (L.-W. Wang et al., 2015) (S. Liu et al., 2012) (Faghih Mohammadi Jalali & Heidari, 2020) (Javed, Zhu, et al., 2020). The electric energy consumption is forecasted by Hamzacebi & Es (2014) using an optimised Grey Modeling (1,1) forecasting technique for 2013-2025 in Turkey. Based on grey system theory, Guo et al. (2011) proposed a new technique for energy consumption prediction from a residential air source heat pump water heater (ASHPWH). X. Wang et al. (2014) propose an algorithm for predicting subject trends based on the Grey Verhulst Model. The modified G.M. (1,1) with Fourier series in time performs best in model fitting and forecasting among these grey models. S. J. Feng et al. (2012) created the grey model GM(1,1) for China's total energy, coal energy, and clean energy consumption. All three forms of energy consumption are rising, but the clean energy consumption is gaining the upper hand. China's goal of self-sufficiency in both biofuels (fuel ethanol and biodiesel) would remain a struggle. The United States and India will retain their ethanol and biodiesel self-sufficiency, respectively, at least until 2028. Biofuel is more likely to be an extra fuel than an alternative fuel, according to the study (Javed, Zhu, et al., 2020). Javed, Zhu, et al. (2020) optimised the model architecture of an existing grey forecasting model and suggested a new forecasting model. L.-W. Wang et al. (2015) and S. Liu et al. (2012) aimed to rate the performance of Indian mining

and metal firms and analyse and measure the change in productivity in these industries. The study contributes to a better understanding of India's mining industry, which is vital to the country's economy (S. Liu et al., 2012). Faghih Mohammadi Jalali & Heidari (2020) used the grey system theory to forecast Bitcoin's price and changes in their research. Lin et al. (2011) indicated that CO₂ emissions would rise over the next three years in Taiwan. It is a useful reference for the Taiwanese government to develop policies to minimise CO₂ emissions by reducing unnecessary energy use. The study (Lin et al., 2011) used the grey forecasting model to anticipate future CO₂ emissions in Taiwan from 2010 to 2012. Guo et al. (2011) confirm that the Even form of Grey Forecasting model (EGM) is a non-optimised model in its original form. Its optimisation can be improved using conformable fractional accumulation and weighted background value generation. Self-sufficiency is an energy resource, an essential indicator of the gap between energy supply and demand. The biofuel self-sufficiency of these countries is also predicted. The top CO₂-producing countries are not only major polluters, but many of them are also major oil producers. (X. Wang et al., 2014). Studying and understanding their behaviour is important for general readers, environmentalists, biofuel dealers, and energy policymakers. Furthermore, even though grey forecasting models have been widely used in energy projections (including renewable energy), we are aware of only a few instances where they have been used to anticipate biofuels. The current work is notable in theory and application because it is the first attempt to estimate Surface temperature change and CO₂ emission using a unique grey forecasting model, EGM (1, 1, α , θ), which generalised the classical model EGM (1,1).

Methodology

Grey forecasting enables one to extract helpful insights about the future from small data, which can be as small as four and can be used for both short term and long term forecast (D. Lim et al., 2010), (Hamzacebi & Es, 2014), (Tsai et al., 2017), (S. Liu et al., 2020). If one looks at the increasing number of studies involving grey forecasting of energy, one would realise that energy forecasts are a typical problem for grey forecasting theory, especially when the number of observations is small and the distribution of data is undefined (Ofosu-Adarkwa et al., 2020), (Ye et al., 2019), (Ma et al., 2019). Therefore, Suganthi & Samuel (2012) identified grey models as one of the twelve notable energy models. The Even Form of Grey Model with first-order differential equation containing one variable EGM (1,1) (EGM for short) and Discrete Form of Grey Model with first-order differential equation containing one variable DGM (1,1) (DGM for short), are two of the four basic models of grey forecasting theory. EGM is suitable for making predictions through non-exponential increasing data sequence, while DGM is suitable for making predictions through a homogenous exponential data sequence (D. Liu, 2017). DGM and EGM can be considered as different forms of the same model (Naiming & Sifeng, 2005). To execute these models, the minimum requirement for data is at least four, as proven from literature. For instance, Yifan and Julong (2004) studied the impact of variation in the number of data points, ranging from 4 to 10, on the parameters α and β of the grey model GM (1,1). Yao et al. (2009) argue that GM(1,1) requires 4 to 10 samples. Deng (2005) has presented a theorem with proof that establishes that the minimum data required for GM (1,1) is 4. Further, the Principle of Minimum Information is one of the six fundamental principles of Grey System Theory-based modelling (D. Liu, 2017); (Yifan and Julong, 2004) allows the grey forecasting models to execute on a small sample. Thus, it can be argued that GM (1,1) models are appropriate models for forecasting through small data ($n \geq 4$). Further literature (S. J. Feng et al., 2012) suggests that if the parameter α is lesser than 0.3, i.e., $\alpha < 0.3$, GM (1,1) is suitable for mid-long term forecasting. In the current study, the sample size in each case is within the acceptable range, and the parameter α is also within the acceptable range. In the following lines, Even GM (1,1) has been summarised as a special case of the proposed model EGM (1, 1, α , θ) (Javed, Ikram, et al., 2020); (S. Liu et al., 2017).

EGM (1, 1, α , θ)

Raw data contains noise, thus considering its direct use in grey forecasting theory, where the sample size is usually small with significant noise in raw data, can decrease forecast accuracy, Professor Julong Deng introduced the concept of accumulation of raw data (and inverse accumulation of the simulation of raw data) (Deng, 2004). In both Even and Discrete forms of GM (1,1), the data accumulation is usually done through the "once accumulating generation operator" (1-AGO), which is basically a cumulative sum operator. If the sequence of raw data is

$$X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n) \right), x^{(0)}(k) \geq 0 \quad (1)$$

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)) \quad (2)$$

$$\text{where, } x^{(1)}(1) = \sum_{i=1}^k x^{(0)}(i), k = 1, 2, 3, \dots$$

Even though 1-AGO is popular for data in grey prediction approaches, its limitations have prevented the application of GM (1,1) series models in various complicated situations, thus prompting scholars to propose alternative operators for data accumulation. One such fruitful attempt was recently made by Ma et al. (2020), who proposed the operations for the conformable fractional accumulation of raw data and the inverse conformable accumulation of simulated data. Building upon their operators, EGM(1,1) is extended in the current study. Unlike classical model EGM (1,1) where the background value of the model is usually calculated through the mean of two consecutive points on the curve of the 1-AGO data sequence, the current study has applied the concept of white-ization of interval grey number (Javed, Ikram, et al., 2020) (S. Liu et al., 2017) to produce weighted background value. Literature confirms the soundness of weighing the background value (Niu et al., 2006). The complete algorithm of the proposed model EGM (1,1, α , θ) is defined below.

EGM (1, 1, α , θ) represents the even form of a grey model with a first-order differential equation containing one variable and weighted background value containing conformable fractional accumulation. Let the sequence of actual data be

$$X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n) \right), x^{(0)}(k) \geq 0, n \geq 4 \quad (3)$$

And the sequence of conformable fractional accumulated data of $\{X\}^{\left(0\right)}$ be

$$X^{(\alpha)} = \left(x^{(\alpha)}(1), x^{(\alpha)}(2), \dots, x^{(\alpha)}(n) \right)_{(4)}$$

$$x^{(\alpha)}(1) = \sum_{i=1}^k x^{(1)} \left(\frac{x^{(0)}(i)}{i^{1-\alpha}} \right), k = 1, 2, 3, \dots$$

where,

In the classical, even grey model, $\alpha = 1$, however, in EGM(1,1, α , θ), $\alpha \in \left(\text{0},1\right)$.

The Adjacent neighbour average sequence of $\{X\}^{\left(1\right)}$ will be

$$\{Z^{\left(1\right)}\} = \left(\{z^{\left(1\right)}\}(1), \{z^{\left(1\right)}\}(2), \dots, \{z^{\left(1\right)}\}(n) \right) \text{ (5)}$$

$$\frac{\partial \{x^{\left(1\right)}\}(k)}{\partial k} + a \{x^{\left(1\right)}\}(k) = b, k \geq 1 \text{ (6)}$$

$$\{x^{\left(0\right)}\}(k) + a \{z^{\left(1\right)}\}(k) = b \text{ (7)}$$

$$\{[a, b]^T\} = \{[B^T B]^{-1} B^T Y\} \text{ (8)}$$

$$\widehat{x}^{(\alpha)}(k) = \left(\{x^{\left(0\right)}\}(1) - \frac{b}{a} \right) e^{-a(k-1)} + \frac{b}{a}, k = 1, 2, \dots, n \text{ (9)}$$

$$\widehat{x}^{(\alpha)}(k) = \{x^{\left(\alpha\right)}(1)\} \left(\widehat{x}^{(\alpha)}(k) - \widehat{x}^{(\alpha)}(k-1) \right), k = 1, 2, \dots, n; \widehat{x}^{\left(0\right)}(0) = 0 \text{ (10)}$$

$$\widehat{x}^{\left(0\right)}(k) = \{k^{1-\alpha}\} \left(\{x^{\left(0\right)}\}(1) - \frac{b}{a} \right) e^{-a(k-1)}, k = 1, 2, \dots, n \text{ (11)}$$

$$\{X^{\left(0\right)}\} = \left(\{x^{\left(0\right)}\}(1), \{x^{\left(0\right)}\}(2), \dots, \{x^{\left(0\right)}\}(n) \right), \{x^{\left(0\right)}\}(k) \geq 0 \text{ (12)}$$

$$\{X^{\left(1\right)}\} = \left(\{x^{\left(1\right)}\}(1), \{x^{\left(1\right)}\}(2), \dots, \{x^{\left(1\right)}\}(n) \right) \text{ (13)}$$

$$\{x^{\left(1\right)}\}(k+1) = \beta_1 \{x^{\left(1\right)}\}(k) + \beta_2 \text{ (14)}$$

$$\{[\beta_1, \beta_2]^T\} = \{[B^T B]^{-1} B^T Y\} \text{ (15)}$$

$$\widehat{x}^{\left(1\right)}(k) = \beta_1 \{k\} \left(\{x^{\left(0\right)}\}(1) - \frac{\beta_2}{1-\beta_1} \right) + \frac{\beta_2}{1-\beta_1}, k = 1, 2, \dots, n \text{ (16)}$$

$$\widehat{x}^{\left(0\right)}(k) = \widehat{x}^{\left(1\right)}(k) - \widehat{x}^{\left(1\right)}(k-1), k = 1, 2, \dots, n; \widehat{x}^{\left(0\right)}(0) = 0 \text{ (17)}$$

$$\widehat{x}^{\left(0\right)}(k) = (\beta_1 - 1) \left(\{x^{\left(0\right)}\}(1) - \frac{\beta_2}{1-\beta_1} \right) \beta_1^{k-1}, k = 1, 2, \dots, n \text{ (18)}$$

Data

There has been a rise in temperature around the world since the 1980s. Developments in Europe, North America, and Asia are particularly notable, where there are sometimes significant temperature increases. On the other hand, in the countries of Oceania, the trend has even been declining for several years. Antarctica is not included here due to a lack of consistent data series. However, there too we can clearly observe a stagnation in the temperature increase (with restrictions). The Germanwatch Institute presented the Global Climate Risk Index 2020. Due to the impacts of extreme weather, the places most affected today by climate change are Japan, the Philippines, and Germany (Eckstein, 2019, p. 20).

The balance between entering and exiting energy is an essential factor for the earth's temperature. Natural and human factors can disrupt the earth's energy balance. Greenhouse gas emissions have increased the greenhouse effect, causing the earth's surface temperature to rise (US EPA, 2017), (Melillo et al., 2014), (Stocker et al., 2013), ASCC (2010). The most important GHGs directly emitted by humans include carbon dioxide (CO₂), methane (CH₄), nitrous oxide (N₂O), and several others. The sources and recent trends of these gases are detailed below. Level of CO₂ increases in the atmosphere by the burning of fossil fuels, trees, waste and biological materials, and the manufacture of cement. Carbon dioxide levels decrease in the atmosphere when plants absorb it as part of the biological carbon cycle. (US EPA, 2015), ("Global Emissions," 2021). CO₂ accounts for about 80 percent of total greenhouse gas emissions in 2019 (US EPA, 21). China is the world's largest contributor (28%) for CO₂ emissions, followed by the USA (15%), India (10%), Russia (5%), Japan (3%), and Germany (2%); these together contribute around 63 percent in total CO₂ emissions worldwide (Ortega, 2021), (UCSUSA, 2020). However, surface temperature data for the current study has been collected from FAOSTAT (2021) for the period 2010-20 and CO₂ emission data for the period 2009-2019 from World Data Bank 2021.

Accuracy Measurement Methods

In the literature, various performance measures have been proposed in order to determine the accuracy of the forecasting approaches. In the current study, five performance measures such as normalized mean absolute percentage error (NMAPE), mean absolute percentage error (MAPE), mean square error (MSE), root mean square error (RMSE), and normalized root mean square error (NRMSE) has been used to measure the accuracy of GM (1,1) and EGM (1,1, α , θ). The following equations show the calculation of the performance measures:

The Mean Square Error is

$$\text{MAPE} = \frac{1}{N} \sum_{t=1}^N \left| \frac{A_t - F_t}{A_t} \right|$$

$$\text{NMAPE} = \frac{1}{n} \sum_{k=1}^n \left| \frac{y_{\text{left}(t\text{right})} - \widehat{y}_{\text{left}(t\text{right})}}{\frac{1}{n} \sum_{k=1}^n y_{\text{left}(t\text{right})}} \right|$$

$$\text{MSE} = \frac{1}{N} \sum_{t=1}^N (A_t - F_t)^2$$

Where, A_t = Actual values at data time t , and F_t = forecast value at data time t

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (\text{left}(y_{\text{right}}) - \widehat{y}_{\text{left}(t\text{right})})^2}$$

Where N denotes the number of samples, is the model forecast value, is the real value, and is the mean value of y_t .

$$\text{NRMSE} = \frac{\sqrt{\sum_{i=1}^N (\text{left}(y_{\text{right}}) - \widehat{y}_{\text{left}(t\text{right})})^2}}{\sqrt{\sum_{k=1}^N (\text{left}(y_{\text{right}})})^2}}$$

Results And Discussion

CO₂ emission is usually considered when producing energy and environmental efficiency evaluation of transportation systems because of its essential role as a symbol of unwanted output (Chang et al., 2013) (Wu et al., 2016). The literature always considers CO₂ emission as deterministic, although it is challenging to develop a proper method to obtain correct CO₂ emission data due to its spatial and temporal variability (Monni et al., 2004). It is challenging to define the consequence of increased CO₂ on climate based on observational data (Wigley & Schlesinger, 1985). As a result, the energy balance model (EBM) has been frequently used to assess this impact (Crowley, 2000) (Hegerl et al., 2006). Chen et al. (2014) concluded that the temperature changes in Asia and North America are susceptible to CO₂ emission. However, accurate prediction of CO₂ emission and surface temperature is known as one of the important indicators for policymakers. Saleh et al. (2016) have suggested a support vector machine to forecast CO₂ emission. The application of a hybrid SVM approach was also used by Ehteram et al. (2021). (Villa et al., 2018), (Noori et al., 2017) (H. S. Lim et al., 2021) suggest different time series based models to forecast surface temperature. While the application of Grey System prediction theory have been known for their reliable predictions with the dataset containing uncertainty or unexpected fluctuation (Liu, 2017) (Javed & Liu, 2018). This section has discussed the grey forecasting model EGM (1,1, α, θ) to evaluate the six leading CO₂ emitting countries and their increasing surface temperature: China, Germany, India, Japan, Russia, and the USA. China is projected to increase surface temperature by 4.75 Celsius and 7.52 metric tons per capita in 2028; thus, China should focus on reducing CO₂ emission and surface temperature to sustain long-term sustainable development, as shown in Fig. 1 and Table 1. Generally, the trend is increasing; however, this increasing trend is relatively more for surface temperature than CO₂ emission. Germany is projected to produce 8.55 metric ton CO₂ emissions per capita, which will increase surface temperature by 6.07 Celsius by 2028, as shown in table 1. Further, as shown in Fig. 2, positive changes in CO₂ emissions are almost stagnant, while surface temperature is rapidly changing. It is important for German policymakers to decide to maintain the changes in surface temperatures.

Although an economic shutdown, renewable energy use has led to reduced CO₂ emissions in four decades in India for some time (IEA, 2020). But a study conducted by Koshy (2021) said that India's CO₂ emission rose faster than that the world average. In the current study, India is expected to produce CO₂ emissions of 2.95 metric tones per capita and 3.58 Celsius increase in surface temperature. As Fig. 3 shows, there is a large fluctuation in the actual value of India's surface temperature, which explains a relatively larger error in the prediction. CO₂ emission per capita in metric tones in Japan is projected to be 8.90, followed by 10.77 in Russia and 13.48 in USA by 2028. They are top in per capita CO₂ emission worldwide, as shown in table 2-3. There is an urgent requirement to take immediate actions to manage climate change and mitigate greenhouse gases (GHGs).

To accomplish the target of carbon neutrality, a downward modification of economic growth is essential, which will help the country decrease pollution emissions. Japan is trying to use innovative ideas to reduce CO₂ emission, especially in the iron and steel industries (Tanaka, 2012) through supply chains (Nishitani et al., 2016) and other initiatives (Shimada et al., 2007). Russia has also taken the initiative to reduce black CO₂ emissions (Kholod & Evans, 2016), and Russia needs to be careful about implementing environmental policy (Tsopanova & Kharitonova, 2020). The rapid improvement in economic activities has largely contributed to environmental distractions (Umar et al., 2020).

Table:1 China and Germany surface Temperature change and CO₂ emission

Surface Temperature (Celsius)						CO ₂ emission (metric tons per capita)							
China			Germany			China			Germany				
Year	Actual	GM(1,1)	EGM (1,1, α , θ)	Actual	GM(1,1)	EGM (1,1, α , θ)	Year	Actual	GM(1,1)	EGM (1,1, α , θ)	Actual	GM(1,1)	EGM (1,1, α , θ)
2010	0.98	0.98	0.98	0.20	0.20	0.20	2009	5.70	5.70	5.70	9.77	9.77	9.77
2011	0.81	0.82	0.81	1.12	1.16	1.12	2010	6.21	6.66	6.65	10.30	10.27	10.23
2012	0.65	0.90	0.90	1.35	1.27	1.24	2011	6.82	6.70	6.70	10.01	10.16	10.13
2013	1.10	1.00	1.00	0.58	1.40	1.37	2012	6.96	6.75	6.74	10.05	10.06	10.03
2014	1.11	1.10	1.12	2.52	1.55	1.51	2013	7.04	6.79	6.79	10.24	9.96	9.93
2015	1.34	1.21	1.24	1.67	1.70	1.67	2014	7.02	6.84	6.84	9.73	9.86	9.83
2016	1.38	1.34	1.38	1.99	1.87	1.85	2015	6.88	6.89	6.88	9.73	9.77	9.73
2017	1.64	1.48	1.53	1.65	2.06	2.04	2016	6.76	6.93	6.93	9.74	9.67	9.63
2018	1.42	1.63	1.70	2.40	2.27	2.25	2017	6.86	6.98	6.98	9.52	9.57	9.54
2019	1.47	1.80	1.88	2.34	2.50	2.49	2018	6.97	7.03	7.02	9.09	9.48	9.44
2020	1.70	1.99	2.09	2.52	2.76	2.75	2019	7.10	7.08	7.07	8.40	9.38	9.35
2021		2.20	2.31		3.03	3.04	2020		7.13	7.12		9.29	9.26
2022		2.42	2.57		3.34	3.35	2021		7.17	7.17		9.20	9.17
2023		2.68	2.84		3.68	3.70	2022		7.22	7.22		9.11	9.08
2024		2.96	3.15		4.05	4.09	2023		7.27	7.27		9.02	8.99
2025		3.26	3.49		4.46	4.51	2024		7.32	7.32		8.93	8.90
2026		3.60	3.87		4.91	4.98	2025		7.37	7.37		8.84	8.81
2027		3.98	4.29		5.41	5.50	2026		7.42	7.42		8.75	8.72
2028		4.39	4.75		5.96	6.07	2027		7.47	7.47		8.66	8.64
2029		4.85	5.27		6.56	6.70	2028		7.52	7.52		8.58	8.55
a; β_1		-0.10	-0.10		-0.10	-0.10	a; β_1		-0.01	-0.01		0.01	0.01
b; β_2		0.68	0.66		1.08	1.04	b; β_2		6.60	6.59		10.41	10.37
α			0.98			0.99	α			1.00			1.00
θ			0.70			0.71	θ			0.59			0.12

A study conducted by (Yang et al., 2021) suggested that in the long-run output, renewable energies, green growth, and globalisation are significant factors in affecting CO₂ emission in the USA. Beijing has taken the initiative to control the growth of private vehicles to reduce CO₂ emissions (Li & Jones, 2015). As shown in Fig. 4-6 (right-Fig.), the trend of CO₂ emission in Japan, Russia, and the USA is moving in a downwards direction and is expected to decrease in significant proportions in the long run. Different studies have explained that unanticipated circumstances such as financial crises or natural hazards can affect emission patterns, even disturbing coordinated efforts to reduce GHG emissions or achieve decarbonisation (Peters et al., 2012), (Fang et al., 2019), (Long et al., 2021).

Table:2 India and Japan surface Temperature change and CO₂ emission.

Surface Temperature (Celsius)							CO ₂ emission (metric tons per capita)						
India			Japan				India			Japan			
Year	Actual	GM(1,1)	EGM (1,1,α,θ)	Actual	GM(1,1)	EGM (1,1,α,θ)	Year	Actual	GM(1,1)	EGM (1,1,α,θ)	Actual	GM(1,1)	EGM (1,1,α,θ)
2010	1.10	1.10	1.10	0.90	0.90	0.90	2009	1.32	1.32	1.32	9.04	9.04	9.04
2011	0.32	0.37	0.34	0.58	0.50	0.46	2010	1.36	1.38	1.37	9.44	9.94	9.92
2012	0.45	0.43	0.39	0.37	0.55	0.51	2011	1.41	1.44	1.44	9.84	9.88	9.85
2013	0.40	0.50	0.45	0.60	0.61	0.56	2012	1.53	1.51	1.50	10.17	9.82	9.79
2014	0.49	0.58	0.51	0.53	0.68	0.63	2013	1.59	1.58	1.58	10.25	9.76	9.73
2015	0.65	0.67	0.59	0.82	0.75	0.69	2014	1.69	1.64	1.65	9.85	9.70	9.67
2016	1.05	0.77	0.68	1.30	0.84	0.77	2015	1.72	1.72	1.73	9.55	9.64	9.61
2017	0.95	0.89	0.78	0.77	0.93	0.85	2016	1.81	1.79	1.81	9.42	9.58	9.55
2018	0.86	1.03	0.89	0.90	1.03	0.95	2017	1.84	1.87	1.89	9.31	9.52	9.49
2019	0.77	1.19	1.02	1.25	1.14	1.05	2018	1.92	1.96	1.98	8.93	9.46	9.43
2020	0.46	1.38	1.18	1.41	1.26	1.16	2019	1.91	2.04	2.07	8.72	9.40	9.37
2021		1.60	1.35		1.40	1.29	2020		2.13	2.16		9.34	9.31
2022		1.85	1.55		1.55	1.43	2021		2.23	2.26		9.28	9.25
2023		2.14	1.79		1.71	1.59	2022		2.33	2.36		9.22	9.19
2024		2.47	2.05		1.90	1.76	2023		2.43	2.47		9.17	9.13
2025		2.86	2.36		2.10	1.95	2024		2.54	2.58		9.11	9.07
2026		3.31	2.71		2.33	2.16	2025		2.65	2.70		9.05	9.02
2027		3.83	3.11		2.58	2.40	2026		2.77	2.82		9.00	8.96
2028		4.43	3.58		2.86	2.66	2027		2.89	2.95		8.94	8.90
2029		5.13	4.11		3.17	2.95	2028		3.02	3.08		8.88	8.85
a; β1		-0.15	-0.14		-0.10	-0.10	a; β1		-0.04	-0.04		0.01	0.01
b;β2		0.18	0.16		0.38	0.34	b;β2		1.30	1.28		10.00	10.03
α			1.00			1.00	α			0.99		1.00	
θ			1.00			1.00	θ			0.68		0.00	

Russia plays an important role in global climate change with the largest land area, a forest area of around 871 million hectares and 221 million hectares of agricultural land. Its GHG emissions peaked in 1990. However, GHS emissions declined by 53% in 2000. Restrictions in the Russian economy, including structural and technological change, was a primary indicator to reduce GHG emissions. This country plays an important role in mitigating climate change, and there is a need to take sufficient initiative to reduce CO₂ emissions (Safonov et al., 2020). Generally, the trend is increasing for Surface temperature in Japan, Russia, and the USA. However, the trend is relatively less predictable compared to CO₂ emission in these countries, which will yield a larger error in the forecasting process of surface temperatures.

Table:3 Russia and USA surface Temperature change and CO₂ emission.

Surface Temperature (Celsius)							CO ₂ emission (metric tons per capita)						
Russia			USA				Russia			USA			
Year	Actual	GM(1,1)	EGM (1,1,α,θ)	Actual	GM(1,1)	EGM (1,1,α,θ)	Year	Actual	GM(1,1)	EGM (1,1,α,θ)	Actual	GM(1,1)	EGM (1,1,α,θ)
2010	0.89	0.89	0.89	0.69	0.69	0.69	2009	10.67	10.67	10.67	17.93	17.93	17.93
2011	1.71	1.64	1.61	0.54	0.83	0.73	2010	11.24	11.45	11.44	18.44	18.23	18.16
2012	1.94	1.72	1.69	1.45	0.92	0.82	2011	11.59	11.42	11.40	17.86	17.93	17.86
2013	1.18	1.80	1.77	0.62	1.01	0.91	2012	11.67	11.38	11.36	17.09	17.63	17.57
2014	1.77	1.89	1.86	0.50	1.12	1.01	2013	11.22	11.34	11.32	17.43	17.34	17.28
2015	2.26	1.98	1.95	1.53	1.24	1.12	2014	11.21	11.30	11.28	17.45	17.06	17.00
2016	2.47	2.07	2.04	2.23	1.37	1.25	2015	11.19	11.26	11.25	16.87	16.78	16.72
2017	2.14	2.17	2.14	1.44	1.51	1.39	2016	11.14	11.23	11.21	16.38	16.50	16.44
2018	2.06	2.28	2.25	1.28	1.67	1.55	2017	11.31	11.19	11.17	16.16	16.23	16.17
2019	2.19	2.39	2.36	1.04	1.84	1.73	2018	11.61	11.15	11.13	16.59	15.96	15.91
2020	3.70	2.50	2.47	1.33	2.03	1.92	2019	11.51	11.12	11.10	16.06	15.70	15.65
2021		2.62	2.59		2.25	2.14	2020		11.08	11.06		15.44	15.39
2022		2.75	2.72		2.48	2.38	2021		11.04	11.02		15.19	15.14
2023		2.88	2.85		2.74	2.65	2022		11.01	10.99		14.94	14.89
2024		3.02	2.99		3.03	2.95	2023		10.97	10.95		14.69	14.65
2025		3.16	3.13		3.35	3.28	2024		10.93	10.91		14.45	14.41
2026		3.31	3.28		3.70	3.66	2025		10.90	10.88		14.21	14.17
2027		3.47	3.44		4.08	4.07	2026		10.86	10.84		13.98	13.94
2028		3.64	3.61		4.51	4.53	2027		10.82	10.80		13.75	13.71
2029		3.81	3.79		4.98	5.04	2028		10.79	10.77		13.52	13.48
a; β1		-0.05	-0.05		-0.10	-0.11	a; β1		0.00	0.00		0.02	0.02
b;β2		1.56	1.53		0.72	0.62	b;β2		11.51	11.49		18.68	18.61
α			1.00			1.00	α			1			1.00
θ			0.76			1.00	θ			0			0.27

The accuracy level of the grey system theory models: GM (1, 1) and EGM (1, 1, α, θ) has been shown in Table 4 & 5. Table 4 & 5 show that all accuracy indicators are almost relatively low with proposed new grey theory approach EGM (EGM (1,1,α,θ)).

Table4: Evaluation of in-sample and out-of-sample Forecast Accuracy of the models.

		In-sample testing (2010-18) of Surface Temperature						Out-of-sample testing (2019-20) of Surface Temperature					
		NMAPE	MAE	MAPE	MSE	RMSE	NRMSE	NRMSE	NMAPE	MAE	MAPE	MSE	RMSE
China	EGM(1,1)	9.33	0.11	11.01	0.02	0.14	0.12	0.19	16.59	0.31	19.58	0.10	0.31
	EGM (1,1, α,θ)	8.79	0.11	10.37	0.02	0.15	0.12	0.25	21.34	0.40	25.19	0.16	0.40
Germany	EGM(1,1)	16.97	0.32	28.16	0.23	0.48	0.29	0.08	4.97	0.20	8.24	0.04	0.20
	EGM (1,1, α,θ)	16.50	0.32	27.38	0.23	0.48	0.29	0.08	4.74	0.19	7.86	0.04	0.20
India	EGM(1,1)	22.65	0.10	14.63	0.02	0.13	0.20	1.16	196.54	0.67	126.97	0.51	0.71
	EGM (1,1, α,θ)	19.89	0.10	12.85	0.02	0.15	0.23	0.87	145.68	0.48	94.11	0.29	0.54
		In-sample testing (2009-17) of CO ₂ emission						Out-of-sample testing (2017-19) of CO ₂ emission					
		NMAPE	MAE	MAPE	MSE	RMSE	NRMSE	NRMSE	NMAPE	MAE	MAPE	MSE	RMSE
China	EGM(1,1)	0.41	0.19	2.80	0.05	0.22	0.03	0.01	0.08	0.04	0.53	0.00	0.04
	EGM (1,1, α,θ)	0.41	0.19	2.80	0.05	0.22	0.03	0.01	0.08	0.04	0.53	0.00	0.04
Germany	EGM(1,1)	0.10	0.10	0.97	0.02	0.13	0.01	0.09	0.80	0.68	7.97	0.56	0.75
	EGM (1,1, α,θ)	0.09	0.09	0.94	0.02	0.13	0.01	0.08	0.77	0.65	7.59	0.51	0.71
India	EGM(1,1)	0.90	0.02	1.46	0.00	0.03	0.02	0.05	2.73	0.08	4.42	0.01	0.10
	EGM (1,1, α,θ)	0.79	0.02	1.29	0.00	0.03	0.02	0.06	3.42	0.11	5.53	0.01	0.12

Table:5 Evaluation of in-sample and out-of-sample Forecast Accuracy of the models.

		In-sample testing (2010-18) of Surface Temperature						Out-of-sample testing (2019-20) of Surface Temperature					
		NMAPE	MAE	MAPE	MSE	RMSE	NRMSE	NMAPE	MAE	MAPE	MSE	RMSE	NRMSE
Japan	EGM(1,1)	29.38	0.16	21.54	0.04	0.20	0.28	13.41	0.13	9.83	0.02	0.13	0.10
	EGM (1,1, α,θ)	26.11	0.15	19.14	0.04	0.21	0.29	22.91	0.22	16.80	0.05	0.23	0.17
Russia	EGM(1,1)	7.41	0.24	14.39	0.09	0.30	0.16	10.61	0.70	20.62	0.74	0.86	0.29
	EGM (1,1, α,θ)	7.32	0.24	14.22	0.09	0.30	0.16	10.47	0.70	20.34	0.77	0.88	0.30
USA	EGM(1,1)	38.62	0.43	46.30	0.24	0.49	0.41	54.15	0.75	64.91	0.57	0.75	0.64
	EGM (1,1, α,θ)	33.58	0.42	40.25	0.25	0.50	0.42	46.07	0.64	55.23	0.41	0.64	0.54
		In-sample testing (2009-17) of CO ₂ emission						Out-of-sample testing (2018-19) of CO ₂ emission					
		NMAPE	MAE	MAPE	MSE	RMSE	NRMSE	NMAPE	MAE	MAPE	MSE	RMSE	NRMSE
Japan	EGM(1,1)	0.26	0.25	2.53	0.09	0.30	0.03	0.70	0.60	6.84	0.37	0.61	0.07
	EGM (1,1, α,θ)	0.25	0.24	2.44	0.09	0.30	0.03	0.66	0.57	6.47	0.33	0.57	0.07
Russia	EGM(1,1)	0.11	0.15	1.27	0.03	0.16	0.01	0.32	0.42	3.64	0.18	0.42	0.04
	EGM (1,1, α,θ)	0.11	0.14	1.23	0.03	0.16	0.01	0.34	0.44	3.81	0.19	0.44	0.04
USA	EGM(1,1)	0.07	0.20	1.14	0.07	0.26	0.01	0.17	0.49	3.01	0.26	0.51	0.03
	EGM (1,1, α,θ)	0.07	0.20	1.14	0.07	0.26	0.02	0.19	0.54	3.32	0.31	0.56	0.03

Conclusion

The current study predicts changes in surface temperature and CO₂ emissions (per capita) for China, Germany, India, Japan, Russia and USA, six of the world's largest contributors to greenhouse gas (GHG) emissions. The study applies the grey model EGM (1,1, α,θ) which is an even form of the grey model in first order differential equation with one variable and weighted background value that contains conformable fractional accumulations. The results show that the CO₂ emissions and surface temperature increase for the top six countries in terms of emissions follows a similar trend. Apart from India with increasing CO₂ emissions and China with an increasing but near constant emissions, all other countries i.e., Germany, Japan, Russia and USA have a decreasing trend in CO₂ emissions (per capita). The projected emission estimates for 2028, however, are still very high: 8.55 metric tons per capita for China, 7.52 metric tons for Germany, 2.95 for India, 8.85 for Japan, 10.77 for Russia, and 13.48 for USA. The change in surface temperature is more alarming with significant increases in temperature for all the six countries, and the results project increase of 6.70°C by 2028 in China, 7.52°C by 2028 in Germany, 2.95°C in India, 2.66°C in Japan, 3.61° in Russia, and 13.48°C in USA by 2028. This is a concerning issue as surface temperature increases adversely affect economic activities and capabilities

and environmental phenomena (Sharma et al., 2011), (Sardans et al., 2006). This study also finds that the EGM (1,1, α , θ) grey model performs better than the EGM (1,1) grey model in terms of both in-sample and out of sample testing.

The current work is limited to the top six countries in terms of GHG emissions as per the Germanwatch Institute's Global Climate Risk Index 2020. Further studies including the impact of lockdowns on CO₂ emissions, along with predicting the general trend of all the other major GHG emissions. The study can also be extended in scope to include other countries of the world, especially predilections for the major developing countries of the world and oil-exporting countries.

Policy Suggestions

The results of the current study point to an important trend in surface temperature changes, which is a major issue at the global as well as national levels. The increase of surface temperature is an increasingly concerning issue that affects a range of factors that concern human life as well as flora and fauna. These, therefore, in conjunction with GHG and particularly CO₂ emissions, need to be addressed by governments and other stakeholders. The following suggestions are hereby forwarded. First, with reference to GHG and CO₂ emissions, the governments must put into place strategic and comprehensive plans that ensure lower emissions without compromising on the quality of economic growth and human development. Such strategies are already in force in Japan, particularly in the iron and steel industry. More countries should adopt such measures and innovate keeping in mind their local constraints and the larger public interest. Second, to reduce GHG and CO₂ emissions, the governments should take into consideration the risk-reward tradeoff for all the major stakeholders. The adoption of strategies that are based on an active participation of stakeholders will ensure maximum participation and minimum need for control and intervention. Third, to reduce the overall emissions, governments can adopt strategies that are based on the relative contribution of specific sectors. Such an approach will give maximum results with the acknowledgement of target areas and help in devising detailed, innovative and focused solutions.

Fourth, with respect to the rising surface temperatures for nearly all the six countries under study, an attempt must be made to bring down surface temperature, and avoid promotion of industries and sectors that contribute highly to GHG emissions. An important consideration along with reducing GHG emissions, is the increase of forest area and green cover. Finally, to mitigate rising surface temperatures, the governments should focus on switching to renewable energy and low-emission energy sources and roll out such policies in a phased manner. The adoption of a series of detailed and short and medium term phased plans are more effective than broad and vague long term goals.

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Figures

Figure 1

China's Surface Temperature Change (in Celsius-Left-Fig.) & CO₂ Emission Trend (Metric Tons Per Capita-Right-Fig.).

Figure 2

Germany's Surface Temperature Change (in Celsius-Left-Fig.) & CO₂ Emission Trend (Metric Tons Per Capita-Right-Fig.).

Figure 3

India's Surface Temperature Change (in Celsius-Left-Fig.) & CO₂ Emission Trend (Metric Tons Per Capita-Right-Fig.).

Figure 4

Japan's Surface Temperature Change (in Celsius-Left-Fig.) & CO₂ Emission Trend (Metric Tons Per Capita-Right-Fig.).

Figure 5

Russia's Surface Temperature Change (in Celsius-Left-Fig.) & CO₂ Emission Trend (Metric Tons Per Capita-Right-Fig.).

Figure 6

USA's Surface Temperature Change (in Celsius-Left-Fig.) & CO₂ Emission Trend (Metric Tons Per Capita-Right-Fig.).