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Assessing inflation and greenhouse gas emissions interplay via neural network analysis: a comparative study of energy use in the USA, EU, and China

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Abstract

This study examines the relationship between inflation and greenhouse gas (GHG) emissions in three major economies: the United States of America (USA), the European Union (EU), and China. The analysis spans from 1960 to 2021 for the USA and EU, and from 1971 to 2021 for China. A feedforward neural network model, optimized using the Levenberg–Marquardt backpropagation algorithm, was employed to predict GHG emissions based on annual inflation rates and fossil fuel energy consumption. The study integrates historical data on inflation trends with GHG emissions, measured in CO2 equivalents, and fossil fuel energy consumption, expressed as a percentage of total energy use. This multidimensional approach allows for a nuanced understanding of the economic-environmental interplay in these regions. Key findings indicate a nonlinear response of GHG emissions to inflation rates. In the USA, GHG emissions begin to decrease when inflation rates exceed 4.7%. Similarly, in the EU, a steep reduction in emissions is observed beyond a 7.5% inflation rate. China presents a more complex pattern, with two critical inflection points: the first at a 4.5% inflation rate, where GHG emissions start to decline sharply, and the second at a 7% inflation rate, beyond which further increases in inflation do not significantly reduce emissions. A critical global insight is the identification of a uniform inflation rate, around 4.4%, across all regions, at which GHG emissions consistently increase by 1%, hinting at a shared global economic behavior impacting the environment. This discovery is vital for policymakers, emphasizing the need for tailored regional strategies that consider unique economic structures, energy policies, and environmental regulations, alongside a coordinated global approach.

Keywords Inflation, Greenhouse gas emissions, Neural network, Environmental policy, Energy consumption

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Introduction

Background

In the realm of global environmental economics, the confluence of macroeconomic forces and ecological impacts has garnered increasing attention, signaling a pivotal shift in the way economic and environmental policies are conceived and implemented. The recent global economic crisis, marked by high inflation rates, has unfolded concurrently with a significant rise in greenhouse gas (GHG) emissions. This scenario presents a dual challenge, particularly for leading economies such as the United States of America (USA), the People's Republic of China

(China), and the European Union[1] (EU). It underscores the urgency of understanding the complex interactions between fiscal and monetary policies, economic growth, inflation, and their broader implications for GHG emissions. This understanding is critical in developing robust, sustainable economic and environmental strategies [1]. The integration of climate change considerations into macroeconomic policy models is essential. This integration illuminates the intrinsic interplay between economic policy decisions and their environmental consequences, emphasizing the interconnected nature of these domains [2]. Despite the critical importance of understanding how macroeconomic elements influence GHG emissions, this area remains underexplored. This gap in research is primarily due to the intricate and multifaceted nature of the influencing factors.

The drive towards economic stability and environmental sustainability necessitates a deep understanding of the factors contributing to climate change, chief among them being GHG emissions. These emissions, stemming from various economic activities, are pivotal in shaping our planet's future climate scenarios. Recognizing the composition and impact of GHG becomes fundamental in this context. GHGs are not monolithic but a collection of gases that include CO2, N2O, and CH4 [3]. Researchers measure the global warming impact of these gases using carbon dioxide equivalents (CO_2eq). This standardized unit allows for a comparison of the warming impacts of various greenhouse gases. The conversion to CO_2eq depends on each gas's global warming perspective (GWP), which assesses its warming impact compared to CO_2 over a specific timescale, commonly 100 years (GWP100). CO_2 has a GWP of 1, however, N_2O and CH_4 have far greater GWP100 values of 265-298 and 28-36, respectively [4, 5]. CO_2eq emissions can be computed by multiplying the mass of each GHG by its GWP100 value. Total CO_2eq emissions are calculated by adding the individual CO_2eq values for each gas. This method allows for an exhaustive evaluation of the overall warming effect of multiple GHGs, which simplifies the assessment of their combined effect on the environment.

Inflation can influence GHG emissions through multiple pathways rooted in underlying macroeconomic principles and empirical observations. High inflation affects consumer purchasing power, inhibits economic growth, and reduces energy demand and consumption, particularly in the fossil fuel sector. Market volatility limits long-term investments and consumer demand, distressing supply systems. However, excessive inflation might encourage enterprises to cut costs and adopt clean technology, consequently supporting the low-carbon transition. Inflation also affects interest rates, combining economic fluctuation with market responses that influence emission patterns. These factors, both direct and intermediary, significantly sway the correlation between economic activities and emissions levels.

Nevertheless, environmental economists have been actively working to unravel the intricate link between monetary and fiscal policies and GHG emissions [6–8]. The complexity of these interlinked systems, further complicated by variables like technological innovation, consumer behavior, global supply chains, and energy policies, makes comprehensive analysis a daunting task [9]. This is particularly true given the divergent economic and policy trajectories observed in major economies [10]. The role of globalization in shaping these trajectories, as discussed by Frankel, highlights how international economic integration affects environmental policy effectiveness [11]. The International Energy Agency's report provides a sector-specific perspective on emissions in the USA, China, and the EU [12], illustrating how similar economic conditions can lead to varied environmental impacts due to differences in policy approaches and industrial structures.

In the context of ongoing, environmental and economic challenges that are shaping global policies and priorities, the International Energy Agency [12] has revealed the emissions patterns of the world's leading economies: the USA, China, and the EU in which combined they are responsible for nearly 50% of total worldwide emissions in recent years. Also, the report revealed that China is presently the world's largest emitter, responsible for 31% of total global GHG emissions. the USA ranked second, generating 14% of worldwide GHG emissions as of 2021. Meanwhile, the EU contributed 7%.

According to the IEA report, China experienced a marginal decrease of 0.2% in CO2 emissions during the period between 2021 and 2022. The observed reduction in emissions can be attributed to several key factors. Primarily, a decline in energy consumption coupled with a significant shift towards the generation of renewable energy has played a pivotal role. This transition towards cleaner energy sources has effectively mitigated a portion of the emissions traditionally associated with coal production, a well-known major source of greenhouse gases. Conversely, the USA saw a slight increase of 0.8% in emissions, which is considered marginal compared to the percentage increase in previous years. According to the same report, the rise in inflation rates played a major role in this slight increase, as it led to a reduction

[1] In accordance with the datasets utilized in this study, the European Union member states included: Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, and Sweden.

in energy consumption compared to 2019 and 2021. This reduction was particularly notable in coal emissions, while there was a slight increase in natural gas emissions. Moreover, the report revealed that regardless of the massive obstacles such as the oil and gas shortages, hydrocarbon constraints caused by the dry spell, and the shutdown of multiple nuclear units, the EU succeeded in cutting its emissions by 2.5%. The observed decrease can be attributed to a confluence of factors, notably a reduction in overall energy consumption, the implementation of energy efficiency measures, and a strategic pivot towards alternative fuel sources.

Literature

The theoretical background for the relationship between inflation and GHG emissions relies on a wide range of environmental theories. The current study is influenced by one of the most widely known theories in the realm of environmental economics characterized by the Kuznets curve (EKC) hypothesis. The EKC suggests a U-shaped reversal relationship between economic progress and environmental pollution. This theory states that the environment is primarily negatively affected by economic growth but begins to decline after a particular income threshold as countries shift to less polluting economies. The EKC serves as a foundation for examining how inflation affects emissions. High inflation may reduce economic output and consumption, pushing nations backward across the EKC curve and cutting emissions. However, due to nonlinear interactions, the nexus is questionable.

The academic investigation into the relationship between inflation and GHG emissions has produced varied results. On one hand, some studies highlight a direct correlation between high inflation rates and reduced GHG emissions due to dampened industrial and consumer activities [13, 14]. On the other hand, research points to an inverse relationship, suggesting that inflation can drive up energy costs and stimulate investments in energy efficiency, potentially reducing emissions [15, 16]. These conflicting findings indicate a complex and multifaceted relationship that demands a more sophisticated analytical approach. Furthermore, the work of Hamilton on the impact of oil prices on the macroeconomy provides insights into how energy markets can influence inflation and, consequently, environmental outcomes [17].

The contrasting findings regarding the impact of inflation on GHG emissions were recently supported by insights from the Inflation Reduction Act (IRA) [18]. The IRA's influence on GHG emissions is notably intertwined with inflationary trends. While it aims to reduce the costs associated with decarbonization and promote the adoption of clean energy, its effectiveness is significantly shaped by broader macroeconomic factors, including inflation. Manifestations of inflation, such as rising interest rates and increasing costs of materials and labor, have the potential to decelerate the pace of decarbonization. However, the IRA introduces various incentives, like tax credits and grants, specifically designed to counterbalance these challenges posed by inflation. These measures aim to reduce the cost of clean energy technologies, thereby mitigating the adverse effects of inflation on efforts to lower GHG emissions. This situation highlights a complex interaction where, although the IRA contributes to emission reductions, its overall effectiveness is closely linked to the fluctuating economic conditions dominated by inflationary factors.

Building on the nuanced academic discourse surrounding inflation and GHG emissions, Ronaghi et al.'s 2019 study offers a compelling perspective [13]. Analyzing data from 2006 to 2015 within OPEC countries, they investigated the interplay between economic and governance factors against CO2 emissions. Their methodology, encompassing variables like GDP, foreign investment, and governance, alongside advanced statistical models, revealed a nuanced inverse relationship: each 1% increase in inflation corresponded to a 1.19% reduction in CO2 emissions.

Furthermore, Ahmad et al.'s 2020 study delved into the relationship between inflation instability and environmental pollution across 40 Asian economies from 1990 to 2018 [14]. Their analysis focused on variables such as inflation instability, CO2 emissions, and energy consumption, employing statistical techniques like cross-sectional tests, panel unit root tests, cointegration analysis, and FMOLS estimation. Their findings indicate a positive effect of inflation instability on the environment, evidenced by changes in CO2 emission levels. This research adds another layer to the complex interplay between economic factors and environmental outcomes, echoing the diverse perspectives in the field.

Ullah et al.'s 2020 study examined the impact of inflation instability and GDP growth volatility on environmental pollution in Pakistan from 1975 to 2018 [15]. Focusing on variables like inflation instability, GDP volatility, and financial development, the study measured their effects on environmental indicators such as CO2, nitrous oxide, and methane emissions. The study utilized the asymmetric autoregressive (ARDL) statistical method to assess the impacts of both positive and negative inflation shocks. In contrast to the previous findings, they discovered that negative shocks in inflation instability led to an increase in CO2 and nitrous oxide emissions.

In 2021, Musarat et al. conducted a study focused on the Malaysian construction industry to explore the effect of inflation on CO_2 emissions [16]. Recognizing the challenge of directly linking inflation and CO_2 emissions, they employed intermediary variables like construction rates, building material prices, and the value of construction work, alongside inflation as an independent variable and CO_2 emissions as the dependent variable. Their methodological approach, using Spearman correlation to account for the nonlinear relationship between these variables, led to the discovery that low inflation rates correlate with reduced CO_2 emissions. However, their findings also present a paradox: in conditions of high inflation, efforts to curb inflation through economic growth paradoxically lead to an increase in CO_2 emissions, underscoring the intricate and sometimes counterintuitive dynamics at play between economic indicators and environmental impact.

A recent study by Grolleau and Weber explores the relationship between inflation and CO_2 emissions over the period 1970–2020 across 189 countries [19]. The authors utilized fixed effects regressions and panel cointegration tests, uncovering a modest but significant negative correlation between core inflation and CO_2 emissions. The study emphasizes that while inflation impacts emissions, this effect alone is insufficient for recommended CO_2 reduction targets, indicating the need for additional policies.

Research objectives and motivations

The existing research regarding inflation-GHG emissions nexus reveals conflicting findings, highlighting the need for more sophisticated analytical approaches. Current methodologies, though robust, may not fully capture the complex, nonlinear dynamics of the economic-environmental interplay. As the need for advanced analytical methods to address the conflicting findings in the inflation-GHG emissions nexus is evident, machine learning (ML) offers a potential solution in this regard. Although the direct application of ML to study the impact of inflation on GHG emissions is limited in existing literature, its capabilities are well-demonstrated in related fields. ML's proficiency in handling complex, nonlinear data make it a promising tool for unraveling the intricate dynamics of economic and environmental interactions [20, 21].

Although there is a scarcity of studies using ML to assess the direct effect of inflation on GHG emissions in the literature, several studies have employed ML techniques to analyze other aspects influencing GHG emissions. For instance, a study in China used various ML algorithms, including k-nearest neighbors (KNN), to explore the relationship between economic growth, industrialization, and CO_2 emissions, demonstrating the nuanced role of urbanization and industrial development in emission levels [22]. Another research focused on agricultural soils in Canada, employing deep learning models like Long Short-Term Memory (LSTM) to predict CO_2 and N_2O emissions, showcasing ML's ability to handle complex environmental data [23]. Additionally, the Gaussian Process Regression (GPR) method was applied to predict CO_2 emissions, offering a nonparametric approach to understanding emissions dynamics [24].

Addressing gaps found in the literature, this study employs a feedforward neural network model optimized with the Levenberg–Marquardt backpropagation algorithm to assess the effects of inflation on GHG emissions in three major economies: the USA, EU, and China. The selection of the USA, EU, and China for comparative analysis is based on their significant influence in the global economic and environmental spheres. Each of these economies presents a unique mix of economic structures, policy orientations, and environmental challenges, offering a diverse array of scenarios to explore the inflation-GHG emissions interplay [25]. The comparative analysis reveals how the interplay between inflation and emissions varies under different economic structures, policy frameworks, and developmental contexts, providing insights that can inform more targeted policymaking. This comparative analysis aims to shed light on how differing economic contexts and policy frameworks impact the relationship between economic indicators and environmental footprints.

The suggested approach in this study employs advanced machine learning techniques to explore the intricate dynamics between inflation, GHG emissions, and energy consumption, implying a deeper and more nuanced understanding than previous methodologies. Traditional research in this area has often been constrained to examining direct, linear relationships between singular economic indicators and emissions, typically within isolated geographic regions or specific sectors. Such studies, while informative, tend to overlook the complex, nonlinear interactions that exist across global economic and environmental systems.

In stark contrast, this study proposes a holistic framework that integrates a wide array of data points across a broad temporal scale. By leveraging the comprehensive analytical capabilities of machine learning algorithms, this research is poised to uncover subtle, context-specific patterns and trends. Moreover, this approach allows for the examination of feedback loops and indirect effects, such as how inflation-driven economic slowdowns might reduce emissions, or conversely, how rising costs of carbon-intensive energy sources could spur inflation and simultaneously drive shifts towards cleaner alternatives.

By employing this advanced methodology and comparative analysis, the study seeks to provide a more integrated and temporally informed perspective, shedding light on the multifaceted ways in which economic factors, energy use, and environmental outcomes are interlinked. It aspires to contribute to both academic knowledge and policy formulation, particularly in an era where the balance between economic growth and environmental sustainability is becoming increasingly crucial [26]. This research aligns with the calls for an interdisciplinary approach to tackling global environmental challenges, echoing the sentiments of scholars like Rockström et al., who advocate for a comprehensive understanding of the interdependence between economic and ecological systems [27]. Additionally, it draws upon the principles outlined by the United Nations Sustainable Development Goals, particularly Goal 13 on Climate Action, highlighting the critical need for integrated policies that address both economic stability and environmental preservation [28].

The manuscript is structured as follows: "Introduction" section introduces the topic. "Data collection and analysis" section is dedicated to data collection and analysis. The methodology is discussed in "Methods" section. The findings are detailed in "Results" section, while "Discussion" section provides an in-depth discussion of these results. Finally, the conclusion in the last section summarizes the study's main findings and implications.

Data collection and analysis

The research centers on three primary datasets covering the period from 1960 to 2021. These datasets predominantly focus on the regions of the USA, the EU, and China. It is noteworthy that certain data subsets specific to China began in 1971 and 1987.

The inflation dataset highlights the metric of inflation, expressed in terms of consumer prices on an annual percentage basis. The dataset captures the essence of the annual inflation rate, gauged using the Consumer Price Index (CPI). CPI offers insights into the year-on-year percentage alterations in an average consumer's expenditure pattern on a variety of goods and services. The central calculation model employed here is the Laspeyres formula [29]. The data pertaining to the USA and EU span from 1960 to 2021, while for China, they span from 1987 to 2021. The primary source of this information is the World Bank's databank, with the foundational data being derived from the International Monetary Fund's (IMF) International Financial Statistics Archive.

The fossil fuel energy consumption dataset represents the percentage of total energy consumption that arises from fossil fuels. This encompasses energy derivatives such as coal, oil, petroleum, and natural gas products. The dataset for the USA and EU spans from 1960 to 2015, and for China, it starts from 1971 and extends through 2014. These data are extracted from the World Bank's databank, whose roots are traced back to the International Economic Association (IEA) Statistics, copyrighted to the OECD/IEA in 2014.

Finally, the GHG emissions dataset is an amalgamation of annual emission data on greenhouse gases. These emissions are transcribed into CO2 equivalents, covering the expansive timeline from 1850 to 2021. To standardize the emissions data, conversion multipliers sourced from the Intergovernmental Panel on Climate Change (IPCC) methodology in the IPCC AR6 report and based on a 100-year timescale were used [30]. The temporal coverage of this dataset ranged from 1960 to 2021. Our World in Data is the primary source for this information, while the foundational data can be credited to Jones et al. [31]. The dataset seamlessly integrates the national emission records of CO2, CH4, and N2O, inclusive of both fossil fuel combustion and land use derivatives. Table 1 provides an overview of the three primary datasets used in the present research, detailing their essential characteristics for the USA, the EU, and China.

Descriptive data analysis overview

The inflation trends for the EU and USA from 1960 to 2021 and for China from 1987 to 2021 can be found in Fig. 1. The data reflect annual inflation rates, providing insight into the economic fluctuations each region has experienced.

The EU and the USA showed relatively similar patterns of inflation until the late 1980s, with the EU typically exhibiting slightly higher rates. Inflation rates peaked during the mid-1970s, with the EU reaching as high as 13.16% in 1974, coinciding with the global oil crisis, which significantly impacted Western economies. The USA experienced its highest inflation rate in 1980, at 13.55%.

China's data, which began in 1987, present a more volatile inflation landscape with a dramatic spike in the late 1980s and early 1990s, peaking at 24.26% in 1994. This period coincides with China's transition from a planned economy to a more market-oriented economy. Post-1994, China showed a notable stabilization in inflation rates, with occasional fluctuations that reflected various stages of economic policy adjustments and market reforms.

The early 2000s marked a period of relative stability and lower inflation for the EU and the USA, whereas China's rates show a mix of mild inflation and deflation, indicating a diverse impact of global economic conditions on these economies. Notably, in 2009, following the global financial crisis, all three regions reported a

Table 1 Summary of datasets utilized in this study

Dataset name	Variable	Temporal scope (USA & EU)	Temporal scope (China)	Source
Inflation dataset	Annual inflation (consumer prices, %)	1960–2021	1987–2021	World Bank's databank; Original data from International Monetary Fund's International Financial Statistics
Greenhouse gas emissions dataset	Annual greenhouse gas emissions in CO2 equivalents	1960–2021	1960–2021	Our World in Data; Underlying data based on Jones et al. [31]; CO2-equivalent conversions from IPCC AR6 report
Fossil fuel energy consumption dataset	Fossil fuel energy consumption (% of total)	1960–2015	1971–2014	World Bank's databank; Originally sourced from IEA Statistics © OECD/IEA 2014

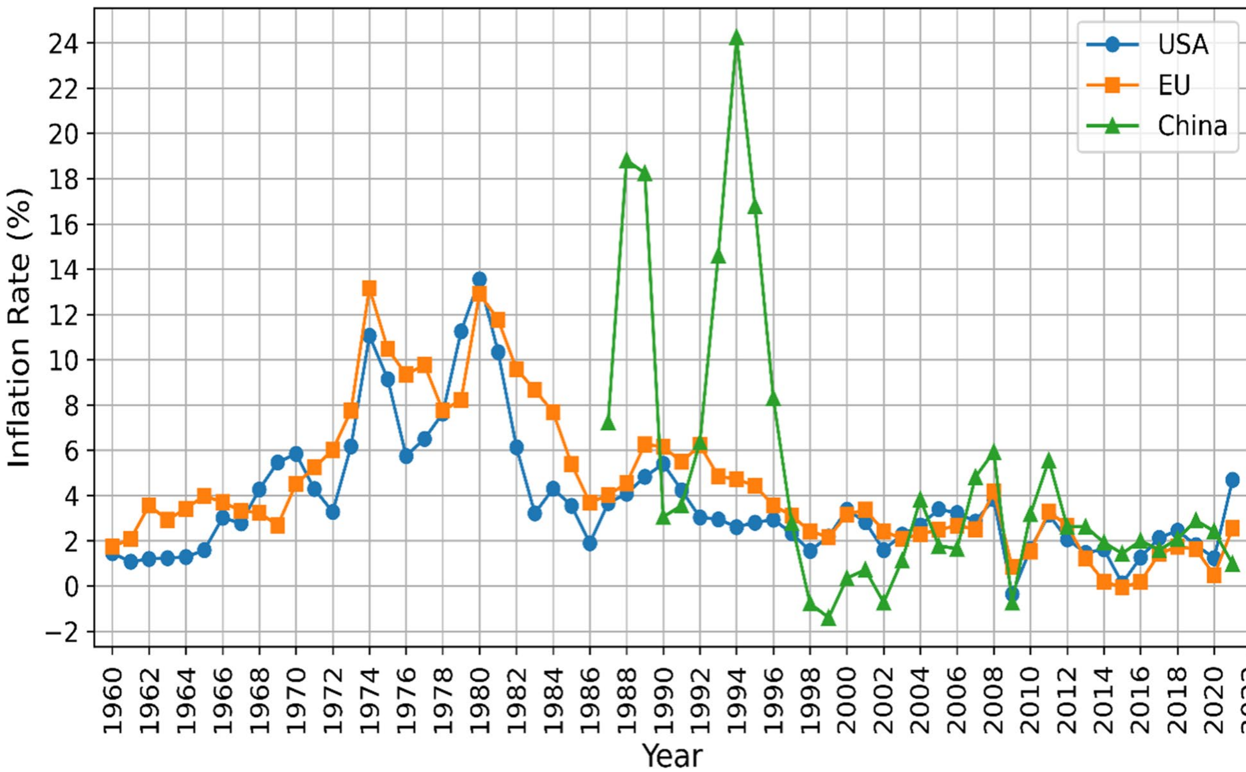

Fig. 1 Inflation trends in the USA, the EU, and China. Source: Authors

drop in inflation rates, with the USA and China even experiencing deflation.

The most recent data from 2020 and 2021 reflect the economic impact of the COVID-19 pandemic, with notable increases in inflation rates.

Annual greenhouse gas (GHG) emission data, measured in CO2 equivalents across the three studied regions spanning from 1960 to 2021, were also collected, as shown in Fig. 2. The EU, starting at 3.7 billion tons of CO2 equivalents in 1960, initially experienced a gradual increase in emissions, reaching a peak in the mid-1970s. A subsequent pattern of decline and fluctuation emerged, reflecting Europe's proactive environmental policies and shifts toward cleaner energy sources.

The US emissions trajectory paralleled that of the EU until the late 1980s, signifying similar industrial and economic growth patterns. However, the USA peaks later, in the early 2000s, reaching more than 7 billion tons of CO2 equivalents, indicating a more prolonged period of high emission levels before showing signs of a downward trend, which is consistent with a shift toward

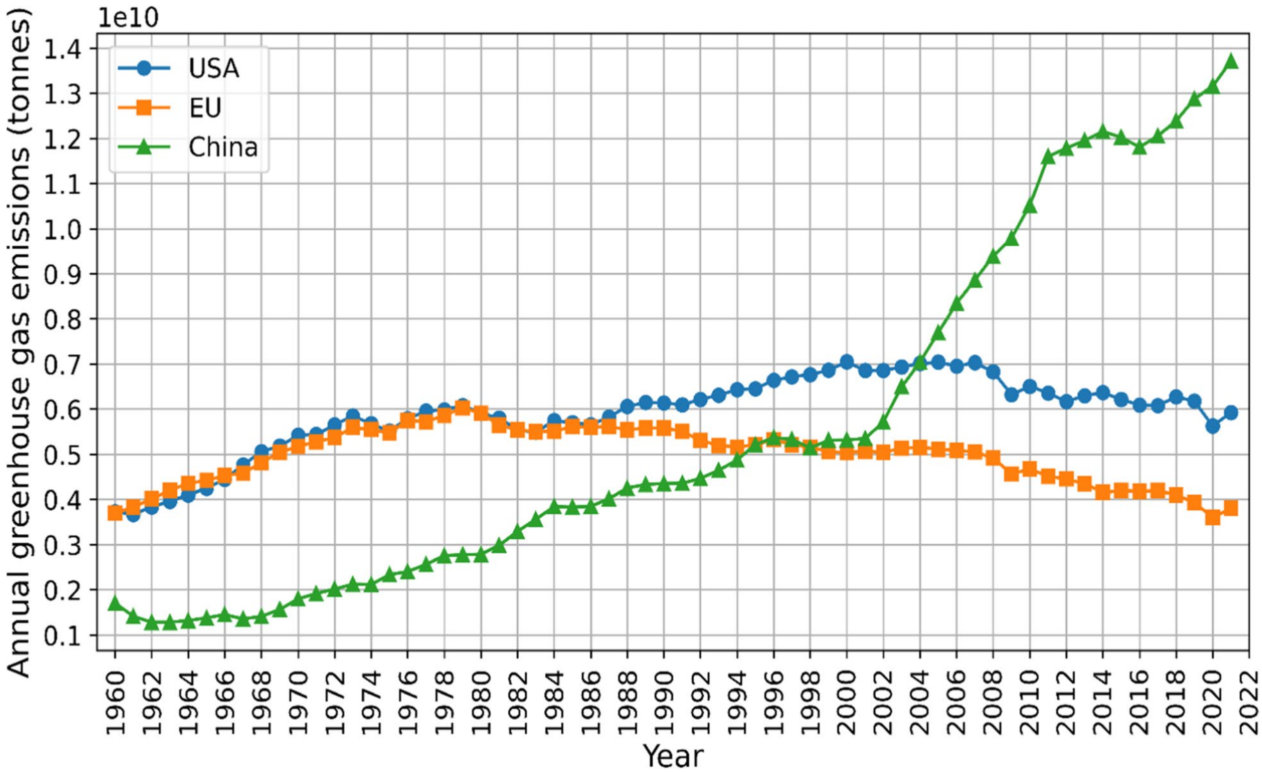

Fig. 2 Annual GHG emissions in the U.S., China, and the EU. Source: Authors

service-oriented economies and increased environmental regulation.

Regarding China's emissions data, the 2000s marked a pivotal point in its rapid industrialization and economic development. The progression is stark, with emissions soaring from 4 billion tons to over 13 billion tons by 2020. This rise reflects China's emergence as a manufacturing powerhouse, with significant implications for global GHG emissions.

Notably, the data highlight a critical point in the early twenty-first century, where China surpassed both the EU and the USA, becoming the largest emitter of GHG. This shift underscores the changing dynamics of global industrialization and the urgent need for environmental policies to address the surge in emissions.

The most recent figures from 2020 and 2021 reveal a decrease in emissions for the EU and USA, likely influenced by the economic slowdown due to the COVID-19 pandemic. Conversely, China's emissions continue to rise, albeit at a slower pace, highlighting the challenges of balancing economic growth with environmental sustainability.

Data on annual fossil fuel energy consumption, expressed as a percentage of total energy use, were collected for the three regions. The figures span from 1960 to 2015 for the EU and USA and from 1971 to 2014 for China, as shown in Fig. 3.

In the 1960s, both the USA and the EU started with fossil fuel energy consumption rates above 93%, indicative of the global reliance on traditional energy sources during this period. Over the following decades, the data reveal a gradual but consistent decline in the USA's and EU's dependence on fossil fuels. This trend reflects the diversification of energy sources, including nuclear power, and increasing investment in renewable energy.

For the EU, the decrease is steady, with a more pronounced decrease beginning in the mid-1970s. By the end of the observation period, the EU's reliance on fossil fuels had decreased to approximately 69.89% by 2015, indicating a significant shift toward alternative energy sources.

The USA exhibits a similar downward trajectory, albeit with slight fluctuations. From a peak in 1966 of approximately 95.96%, there was a noticeable decline to 82.43% by 2015, underscoring policy shifts and technological advancements in energy consumption.

China's data, available from 1971, starts at 59.90%, which is notably lower than that of the USA and EU at that time. However, China's reliance on fossil fuels sharply increased in the following decades, reaching a

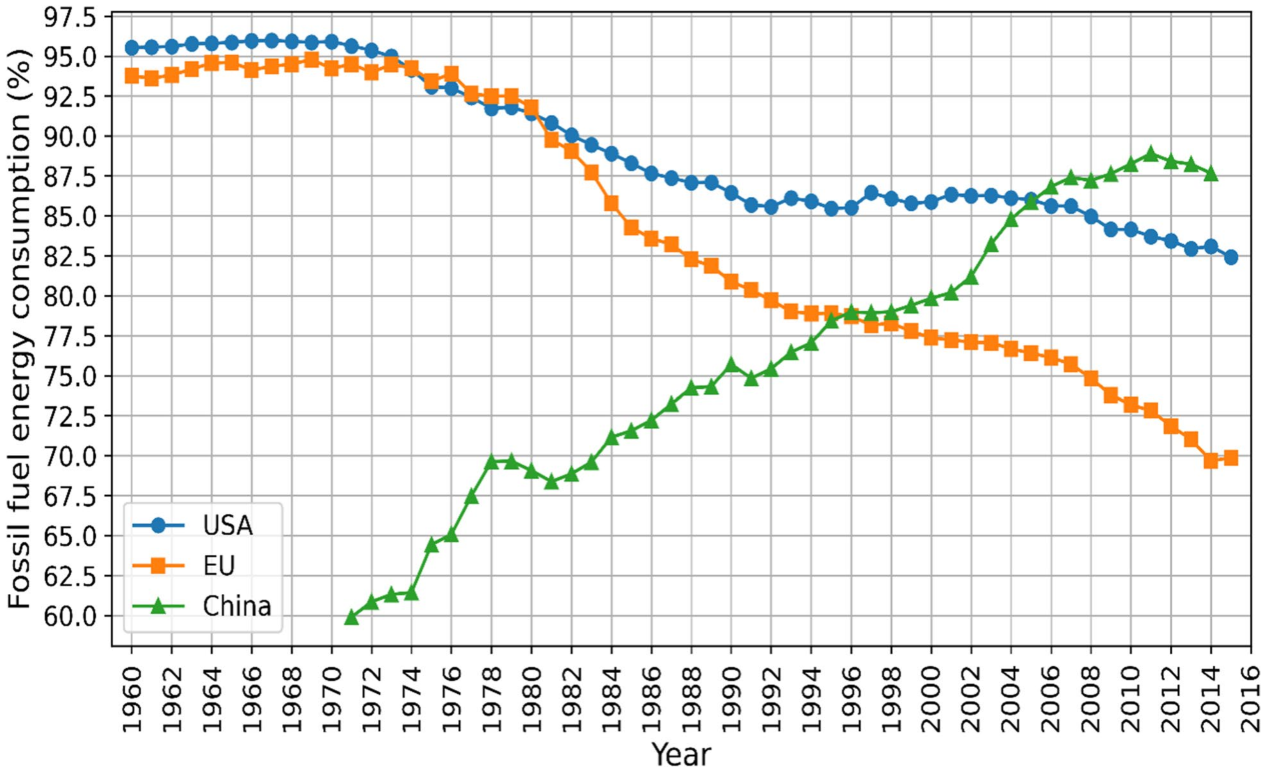

Fig. 3 Fossil fuel energy consumption percentages in the USA, China, and the EU. Source: Authors

peak of 88.90% in 2011. This increase corresponds with China's rapid industrialization and economic development phase, where fossil fuels played a critical role in supporting this growth.

The subsequent minor reduction observed in China's percentage suggested initial steps toward a more balanced energy mix. However, it remains the highest among the three, highlighting its continued dependence on fossil fuels compared to the USA and the EU.

Methods

This study adopted a robust approach to investigate the complex relationships between economic metrics and environmental outcomes. A feedforward neural network model optimized with the Levenberg–Marquardt backpropagation algorithm was utilized to quantitatively assess the effects of inflation on GHG emissions. As illustrated in Fig. 4 which shows the flowchart of the general methods, the selected variables, based on their empirical relevance and data availability, served as input features for the models, ensuring the reliability and comprehensiveness of the results. The annual inflation rate, fossil fuel energy consumption, and annual GHG emissions were used to train three separate Artificial Neural Network (ANN) models for the USA, the EU, and China. These models were subsequently used to predict GHG emissions over a range of inflation values from 0 to 10%, with increments of 0.1%, while holding the fossil fuel energy consumption percentage constant (at the latest available value). This approach allowed for a detailed examination of the relationship between inflation and GHG emissions across different economic contexts. The use of a constant fossil fuel energy consumption percentage across the inflation range ensured that changes in the predicted GHG emissions could be attributed primarily to the variations in inflation.

Feedforward neural network with the levenberg–marquardt backpropagation algorithm

Three different ANN models were developed, each tailored to a specific region: the USA, the EU, and China. These models were trained using a feedforward architecture coupled with Levenberg–Marquardt backpropagation algorithm [32], as illustrated in Fig. 5.

The input data, represented by x, undergo propagation through the network to generate output. The activation vector for any given layer l is defined by Eq. 1:

$$a(1) = x \tag{1}$$

Moreover, the activation is represented using the function described by Eq. 2:

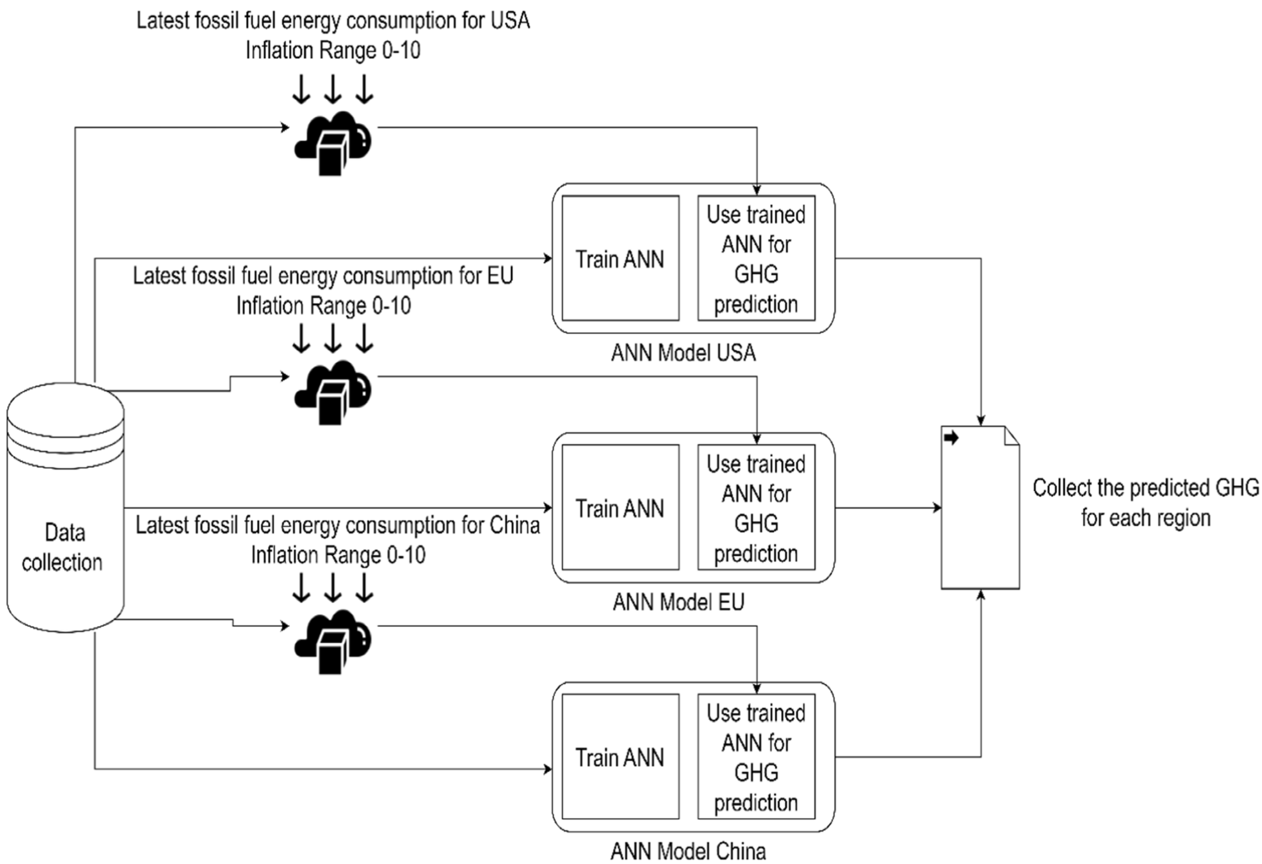

Fig. 4 Flowchart of the general methods. Source: Authors

$$a(l) = \sigma(h(l)) \quad (2)$$

The weighted input for layer l is given by:

$$a(l) = \sigma(w(l-1)a(l-1) + b(l-1)) \quad (3)$$

where the activation vector is denoted as $a(l)$, the weighted input vector as $h(l)$, the weight matrix connecting two consecutive layers as $w(l-1)$, the bias vector of the preceding layer as $b(l-1)$, and the activation function as σ.

Following the feedforward phase, the network's resultant output is juxtaposed against the desired output to discern the error.

Errors for each layer are quantified using:

$$\delta(L) = \nabla h(L)\mathcal{L} \odot \sigma^{'}(h(L)) \quad (4)$$

$$\delta(l) = ((w(l))T\delta(l+1)) \odot \sigma^{'}(h(l)) \quad (5)$$

Here, $\nabla h(L)\mathcal{L}$ is the gradient of the loss with respect to the output of the network. $\delta(L)$ denotes the error at the output layer, while $\delta(l)$ is the error at any layer l. The symbol $\odot$ represents elementwise multiplication, and $\sigma^{'}$ is the derivative of the activation function.

The weights and biases are then updated using the following equations:

$$w^l := w^l - \Delta w^l \quad (6)$$

$$b^l := b^l - \Delta b^l \quad (7)$$

In the training process, the weights and biases for layer l are updated using the regularized Gauss–Newton equation (Eqs. 8 and 9). Regularization ensures that the updates are not pushed to extreme values, promoting stability in the learning process.

$$\Delta w^l = \left(J^T J + \lambda I\right)^{-1} J^T \delta^{l+1} \left(a^l\right)^T \quad (8)$$

$$\Delta b^l = \left(J^T J + \lambda I\right)^{-1} J^T \delta^{l+1} \quad (9)$$

where the weight and bias updates for layer l are represented by Δw^l and Δb^l, respectively. λ is identified as the

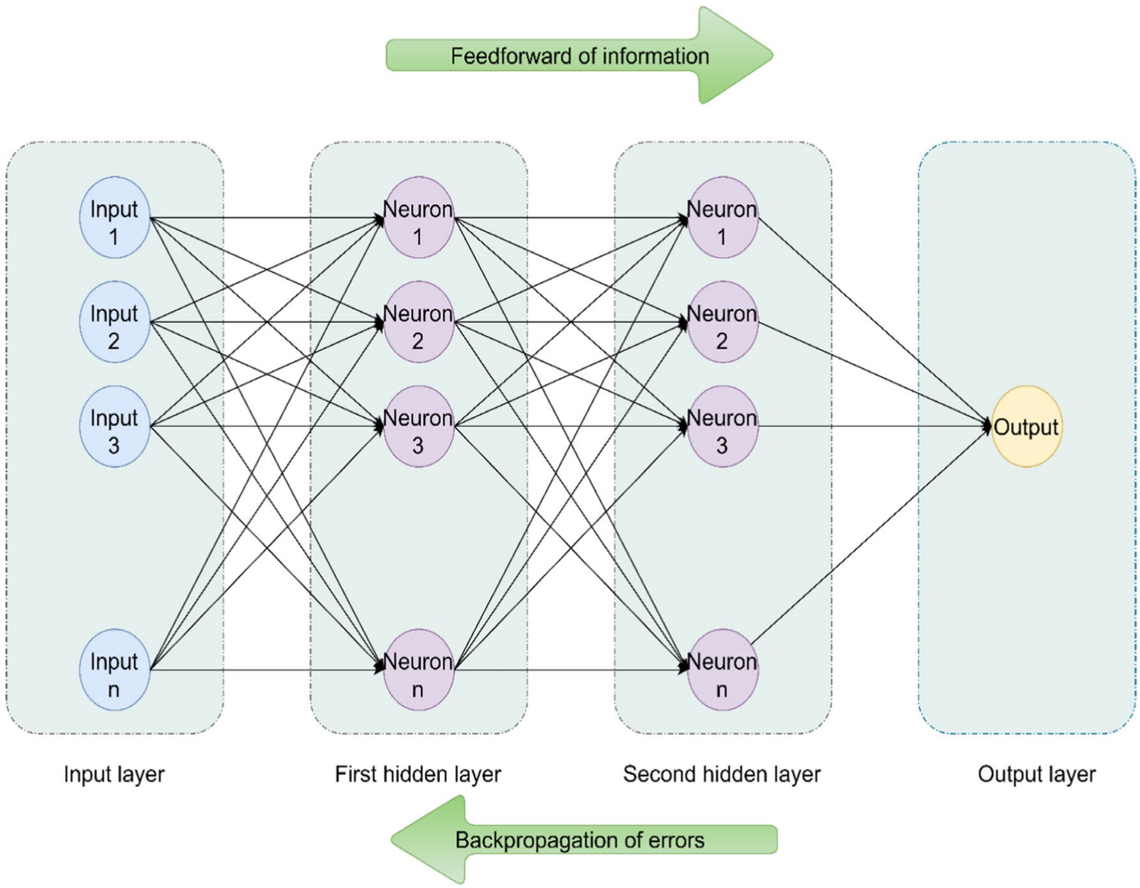

Fig. 5 A feedforward neural network with n inputs and one output. Source: Authors

Levenberg–Marquardt parameter, and J is the Jacobian matrix, which is defined as:

$$\mathrm{J}_{\mathrm{ij}}^{(\mathrm{l})} = \frac{\partial \mathrm{h}_{\mathrm{i}}^{(\mathrm{l})}}{\partial \mathrm{w}_{\mathrm{ij}}^{(\mathrm{l}-1)}} \tag{10}$$

$$= \frac{\partial}{\partial w_{ij}^{(l-1)}} \left(\sum_k w_{ik}^{(l-1)} a_k^{(l-1)} + b_i^{(l-1)} \right) \tag{11}$$

$$= a_j^{(l-1)} \tag{12}$$

$$\delta^{(L)} = J^{(L)} \left(f\left(h^{(L)} \right) - y \right) \tag{13}$$

$$\delta^{(l)} = \left(J^{(l)} \right)^T \left(J^{(l)} \left(J^{(l)} \right)^T + \mu I \right)^{-1} \delta^{(l+1)} \tag{14}$$

$$\frac{\partial E}{\partial w_{ij}^{(l)}} = a_j^{(l-1)} \delta_i^{(l)} \tag{15}$$

$$\frac{\partial E}{\partial b_i^{(l)}} = \delta_i^{(l)} \tag{16}$$

where the error vector at the output layer is represented by $\delta^{(L)}$, the Jacobian matrix of layer l is denoted by $J^{(l)}$, and the regularization parameter that controls the step size is given by μ. I is defined as the identity matrix. The derivative of the cost function with respect to the weights and biases is determined as follows:

$$\frac{\partial E}{\partial w_{ij}^{(l)}} = \frac{\partial E}{\partial h_i^{(l)}} \frac{\partial h_i^{(l)}}{\partial w_{ij}^{(l)}} \tag{17}$$

$$= \delta_i^{(l)} a_j^{(l-1)} \tag{18}$$

Table 2 ANN hyperparameter values and descriptions

Parameter	Description	Tested values during ANN optimization
Number of inputs	Number of input data variables	2
Number of outputs	Number of output forecasted variables	1
Number of hidden layers	Number of hidden layers	1
Number of hidden neurons	Number of hidden neurons	2–20
Maximum epochs	Max. number of training iterations before training is stopped	1000
Performance goal	The minimum target value of MSE	0
Cross-validation	Cross-validation folds to be used during the grid search	5
Termination Error	The threshold where training terminates when the error is less than or equal to it	1e-8

$$\frac{\partial E}{\partial b_i^{(l)}} = \frac{\partial E}{\partial h_i^{(l)}} \frac{\partial h_i^{(l)}}{\partial b_i^{(l)}} \tag{19}$$

$$= \delta_i^{(l)} \tag{20}$$

The weights and biases are then updated using the following rules in each iteration:

$$w_{ij}^{(l)} := w_{ij}^{(l)} - \eta \frac{\partial E}{\partial w_{ij}^{(l)}} \tag{21}$$

$$b_i^{(l)} := b_i^{(l)} - \eta \frac{\partial E}{\partial b_i^{(l)}} \tag{22}$$

Here, the step size of the weight and bias updates is controlled by the learning rate, denoted by η. The algorithm is applied repeatedly until convergence of the error is achieved or until a predefined maximum number of epochs is met.

In this study, a feedforward ANN with Levenberg–Marquardt backpropagation, as described in Eqs. 1–22 [25], is employed in Python. The dataset was partitioned using a 70–30 split for model training and validation. This means that 70% of the collected data was utilized for training the neural network models, while the remaining 30% of the data, which was not exposed to the model during the training phase, was then used to test and evaluate the model's predictive performance. The choice of a Feedforward Neural Network with Levenberg–Marquardt Backpropagation is justified by its superior efficacy in handling complex, non-linear predictive problems. This algorithm combines the advantages of gradient descent for stability and the Gauss–Newton method for speed, leading to more rapid convergence compared to conventional backpropagation techniques. Particularly in data-scarce environments, this method demonstrates exceptional performance, providing a high degree of precision without the need for extensive training datasets, distinguishing it from other machine learning methodologies [33]. The ANN optimization process involved testing various hyperparameters to identify the configuration that yielded the best performance, as detailed in Table 2. The parameters tested included the number of input and output variables, which were two and one, respectively. A single hidden layer was employed, with a range of 2 to 20 neurons explored for optimization. The training process was constrained by a maximum of 1000 epochs and a performance goal set to minimize the mean squared error (MSE) to a target of zero. Additionally, fivefold cross-validation was incorporated during the grid search to validate the model, and training was terminated when the error reached a threshold of 1e-8.

This method involves segmenting the entire dataset into five equal parts and then using each segment in turn as a test set while the remaining data serve as the training set. Importantly, this process was not conducted sequentially but rather by taking chunks of data at random intervals within the time frame, thereby minimizing temporal bias and reflecting more general conditions. This strategy allows our models to train and validate against diverse subsets of data, ensuring that the identified inflation rate thresholds are not artifacts of specific time periods but rather robust indicators that have been validated across various temporal contexts.

Results

The neural network models for predicting GHG emissions from inflation and fossil fuel energy consumption were optimized for each region of interest: the USA, the EU, and China. The optimal network structures were determined by the number of hidden neurons that maximized the coefficient of determination (R^2) between the observed and predicted GHG emissions, with the Root

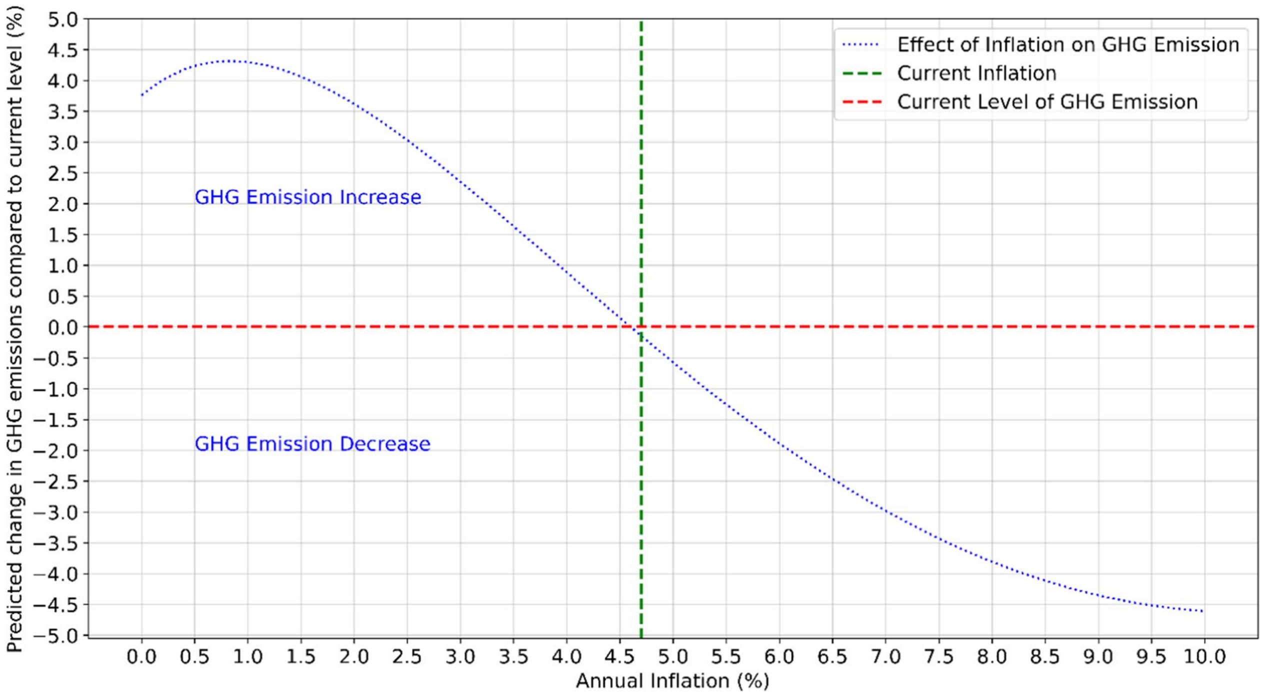

Fig. 6 Projected GHG Emissions Relative to Inflation Rates in the US. Source: Authors

Mean Squared Error (RMSE) used as a measure of model accuracy. The USA model had 14 hidden neurons and an R^2 of 0.88 indicating a high degree of fit and explanatory power with an RMSE value of $9.75 * 10^6$. The EU model had 6 hidden neurons and an R^2 of 0.89, implying a slightly higher accuracy and precision, with an RMSE value of $7.48 * 10^6$. The China model had 2 hidden neurons and an R^2 of 0.87, suggesting that a simple network structure can still capture the significant relationship between the economic and energy consumption variables and GHG emissions, with an RMSE value of $9.79 * 10^6$.

The results from the ANN for the USA show the trend of GHG emissions in relation to inflation rates, which can be found in Fig. 6. As inflation deviates from the current rate of 4.7%, the model predicts varying impacts on GHG emissions. Below the current inflation rate, there is an observed increase in GHG emissions, with the most significant increase of 4.31% occurring at an inflation rate of 0.8%. Conversely, as inflation rates exceed 4.7%, the ANN forecasts a consistent reduction in GHG emissions. The trend suggests a nonlinear response, with emissions reduction gaining momentum as inflation climbs, reaching a decrease of 4.61% at an inflation rate of 10%. This indicates that inflation rates higher than current inflation rates may be associated with factors that lead to lower GHG emissions, such as potential reductions in consumption.

The ANN results for the EU also exhibit a trend toward GHG emissions relative to varying inflation rates, as shown in Fig. 7. When inflation rates are below the current level of 2.5%, the model predicts a steady trend in GHG emissions similar to the current levels. Conversely, as inflation rates rise above the current level, there is a notable shift, with GHG emissions initially decreasing slightly and then decreasing more steeply after crossing the 7.5% inflation rate. This steep increase intensifies as inflation grows, underscoring a significant relationship where higher inflation rates could lead to a substantial decrease in GHG emissions, potentially due to decreased industrial activity and energy consumption.

In Fig. 8, the ANN results for China indicate stable GHG emissions as inflation rates increase to 4.5%, mirroring the current emission trends at an inflation level of 1%. Beyond the 4.5% threshold, GHG emissions begin to decrease, with a sharper decline observed past a 5.5% inflation rate. This notable decrease in emissions continues with rising inflation, emphasizing the significant inverse relationship between higher inflation rates and GHG emissions. The emissions decrease plateau around a 7% inflation rate, where emissions changes remain relatively constant even as inflation increases further.

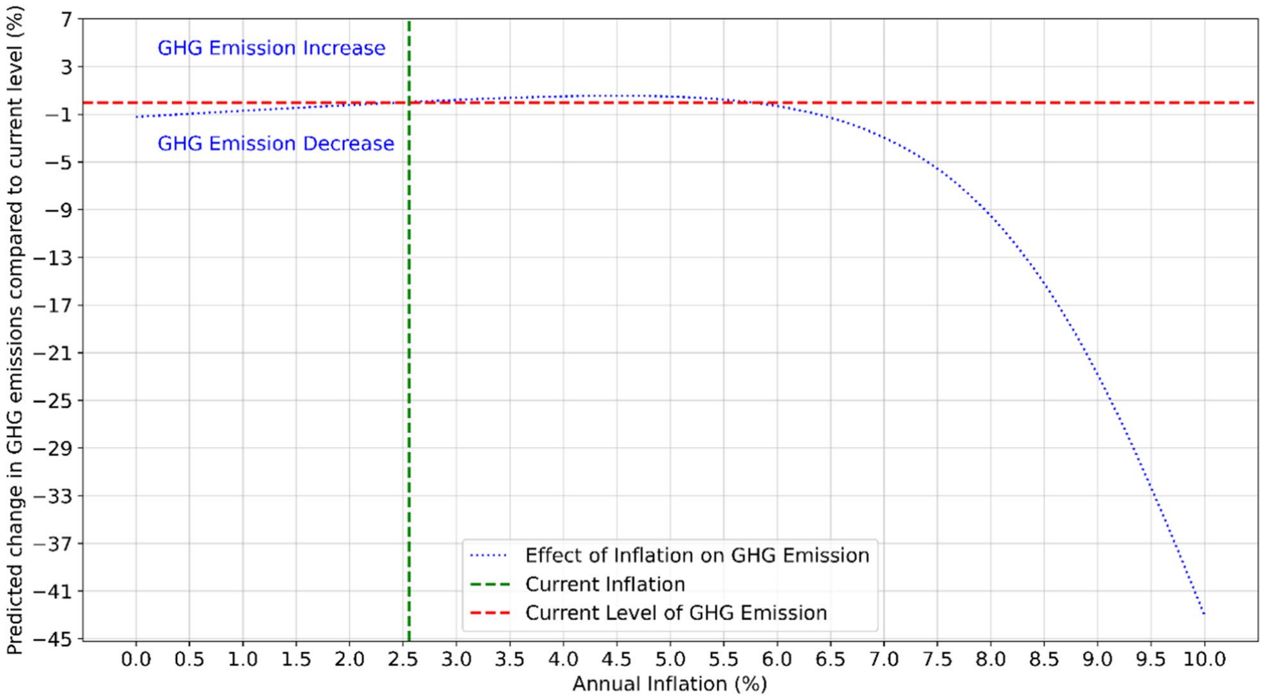

Fig. 7 Projected GHG Emissions Relative to Inflation Rates in the EU. Source: Authors

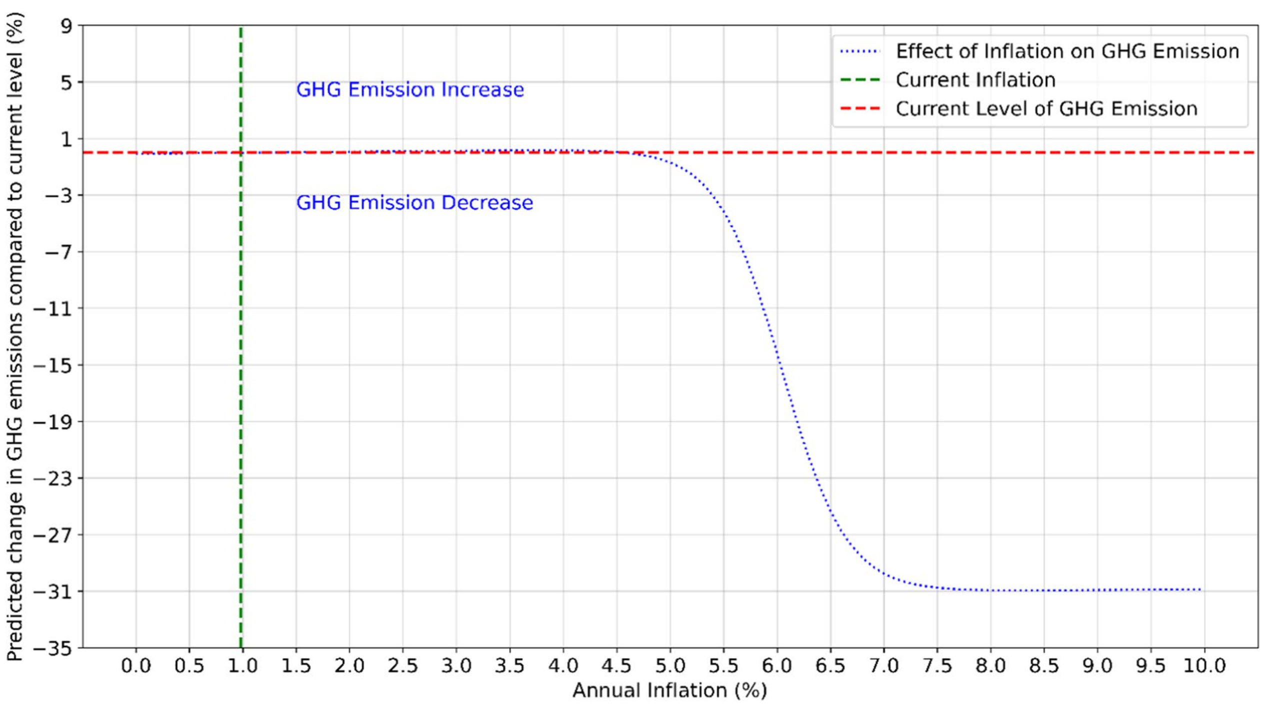

Fig. 8 Projected GHG emissions relative to inflation rates in China. Source: Authors

Discussion

The research presented in this paper examines the predicted changes in GHG emissions in relation to varying levels of inflation for three major economic regions: the USA, the EU, and China. The findings reveal a nuanced relationship between inflation rates and GHG emission

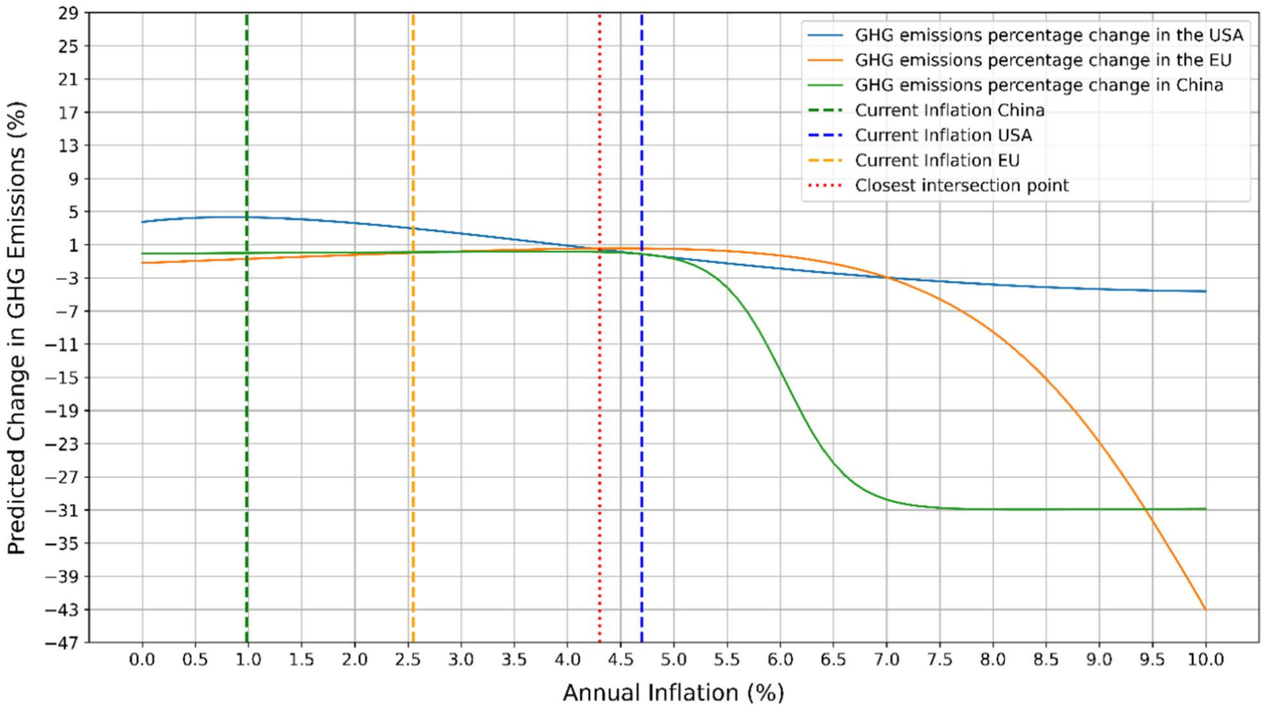

Fig. 9 Comparative analysis of predicted GHG emission changes in response to inflation across the USA, the EU, and China. Source: Authors

changes that differs across these regions, illustrating the complexity of economic-environmental interactions.

Figure 9 integrates the insights of the prior analysis, aligning them on the same scale for direct comparison. A noteworthy observation from Fig. 9 is that across all three studied regions, there is a uniform point where the inflation rate of 4.4% correlates with a consistent 1% increase in GHG emissions. This could suggest potential global economic behavior at this specific inflation rate that uniformly impacts GHG emissions, regardless of regional differences. The consistency of these results warrants further scientific investigation to understand the underlying mechanisms that could influence this phenomenon. This raises questions about the role of economic activities, energy usage, and environmental policies that converge at this inflation rate to produce similar environmental impacts across diverse economies. However, China's pattern differs from that of the USA and the EU, as China has two critical inflection points: the first at 4.5% inflation, where GHG emissions start to decline sharply, and the second at 7% inflation, beyond which additional inflation does not appear to induce further decreases in GHG emissions.

The interplay between inflation and GHG emissions is influenced by a range of factors, such as economic policies, energy consumption patterns, and investments in sustainable technologies [34]. This interplay varies by region, reflecting distinct economic structures, energy policies, and environmental regulations. The unique responses of the USA, the EU, and China to inflation in terms of GHG emissions emphasize the need for tailored regional strategies in climate change mitigation efforts that are in sync with economic objectives and the broader socioeconomic landscape.

The observed negative correlation[2] between inflation and GHG emissions in the USA at lower inflation levels suggests a link between low inflation and higher consumption, possibly due to increased economic activities and consumer demand. As inflation increases, there is a pivot point where the pressures of inflation may prompt cost-cutting measures that could be detrimental to the environment. This could indicate a shift toward more carbon-intensive energy sources as businesses strive to manage increased costs, leading to a decrease in demand and a subsequent reduction in GHG emissions. This relationship highlights the complex interplay between economic forces and environmental impacts, suggesting that inflation can influence environmental outcomes in nonlinear ways. The flattening of GHG emissions in the USA after a certain increase in inflation could be

[2] "negative correlation" used in this study refers to the statistical relationship observed between the two variables: as inflation increases, GHG emissions tend to decrease, based on the data analyzed.

due to a stabilization in the trade-offs between economic growth and environmental impact. As inflation rises, the cost of goods and services typically increases, which can dampen consumer spending and slow economic activity. This slowdown may lead to reduced energy consumption and thus plateauing GHG emissions. Additionally, high inflation can trigger efficiency drives and technological innovations aimed at reducing costs, which may inadvertently reduce emissions. However, this might also mean that any further potential for emission reductions through cost-cutting measures has been exhausted, leading to a steady state of emissions despite further increases in inflation.

In the EU, the results suggest a period of stability where GHG emissions do not significantly change with varying levels of inflation. This plateau in emissions could be reflective of a balance between economic activity and consumption that is maintained despite rising prices. However, the significant decline in emissions after a certain point of almost –43% could be more indicative of inflation's impact on economic production than of the success of environmental policies alone. As a significant importer of energy, the EU's economic activities—and thereby its emissions—may be heavily influenced by the costs of imported energy. When inflation increases, the costs of energy imports increase, leading to reduced consumption and production. This reduction in economic activity, especially in energy-intensive industries, could lead to a sharp decrease in emissions. This does not entirely dismiss the role of environmental policies or consumer behavior in the EU. The region has indeed been proactive in implementing measures such as investing in renewable energy sources, advancing energy-efficient technologies, and promoting sustainable consumption practices. These efforts may contribute to the overall decline in emissions. However, the severity of the decrease suggests that external economic factors, such as inflation impacting energy import costs, play a considerable role.

The EU's sharp decline in GHG emissions raises questions about the long-term sustainability of this trend. If the decline is primarily due to reduced economic activity, there could be a risk of emissions rebounding once economic conditions improve unless there is a concurrent structural shift toward a greener economy. Hence, it is critical for policymakers to differentiate between temporary reductions caused by economic contractions and genuine, lasting decreases achieved through intentional policy actions and structural changes. The challenge for the EU is to ensure that the decline in emissions is not solely a byproduct of economic downturns but also a result of systemic transformation toward sustainability. This involves enhancing energy independence, accelerating the transition to renewable energy, and encouraging energy-saving behaviors that are less vulnerable to inflationary pressures. Policymakers need to carefully analyze emissions trends to craft strategies that maintain the momentum of emissions reduction while fostering economic resilience.

Likewise, the observed shifts in GHG emissions in the EU, as inflation rates fluctuate, could be significantly influenced by the operational dynamics of the EU Emissions Trading System (EU-ETS). EU-ETS is a cornerstone of the European Union's policy to combat climate change, operating as a cap-and-trade system that sets a limit on overall emissions from high-emitting industries and allows companies to buy and sell emission allowances. The EU-ETS might be acting as a moderating force against the backdrop of economic changes. As industries face higher inflation, the cost pressures could drive them to cut down on operations leading to reduced emissions. However, the EU-ETS adds another layer to this scenario. By capping the total level of emissions and allowing trading of emission allowances, the system incentivizes companies to reduce their carbon footprint more aggressively than they might under economic pressure alone. This creates a scenario where, even in varying inflationary environments, the EU-ETS encourages companies to continue investing in cleaner technologies and practices. The trend toward lower emissions at higher inflation rates may not just reflect reduced economic activity but could also indicate a structural change towards sustainability, accelerated by the EU-ETS. In other words, the EU-ETS may help decouple economic growth from GHG emissions, even as it faces the challenges of inflation fluctuation.

In China, the relationship between inflation and GHG emissions shows an initial phase of stability, suggesting that low to moderate inflation does not significantly affect consumption patterns or economic activities in terms of their environmental impact. However, as inflation surpasses a specific threshold, there is a notable decrease in emissions. The nearly 30% reduction in China's GHG emissions associated with high inflation may be attributed more to reduced demand and production rather than to the adoption of more efficient practices or a shift to less carbon-intensive consumption patterns. This significant decrease continues until reaching another point where emissions stabilize, implying a new equilibrium in the cost efficiency and environmental impact of economic activities. In China's case, the stabilization after a significant drop could reflect a saturation point where high inflation may not necessarily result in reduced GHG emissions due to economic resilience and the nature of international trade. Despite inflation, a devalued Yuan could keep exports competitive, sustaining industrial output and its associated emissions. Simultaneously, robust internal demand, fuelled by a large population and urbanization, may continue to drive high energy consumption, often from coal-dependent sources, counteracting any potential emissions reduction from decreased economic activity due to inflation. Moreover, China's efforts to stabilize its economy amidst inflation could involve stimulus measures that bolster production, potentially negating the emission declines typically expected with reduced economic growth.

Across these regions, the key takeaway is that while emissions may decline as a result of economic factors such as inflation, the goal is to achieve reductions through sustainable development and proactive environmental policies. It is essential for policymakers to ensure that the observed emission trends are a result of moving toward a more sustainable and resilient economy and not merely a consequence of economic downturns.

Furthermore, the observed 1% increase in GHG emissions at a 4.4% inflation rate in all the studied regions highlights the need for a global dialog on policy coherence between economic and environmental objectives. This suggests a critical point where the interplay between inflation and GHG emissions intersects across diverse economies, pointing to potential common economic behavior with environmental implications. International cooperation, information exchange, and policy harmonization could be instrumental in understanding and managing the relationship between inflation and GHG emissions. This global approach ensures that individual regions' economic measures do not inadvertently compromise global environmental targets.

The findings of the current study align with the findings of Ronaghi et al. [13], which indicate that a 1% increase in inflation across OPEC nations is responsible for a 1.19% decrease in CO2 emissions. Moreover, the current study findings align with Djedaiet's [35] findings, which, observed that inflation negatively impacts CO2 emissions. It also revealed that inflation shocks asymmetrically affect CO2 emissions, posing challenges for balancing economic stability with environmental sustainability. On the other side, the current study findings are partially contrary to Ullah et al. [15], which indicate that inflation instability impacts environmental quality differently: decreases in inflation (negative shocks) increase CO2 and N2O emissions, while increases in inflation (positive shocks) have negligible environmental effects. Also, the current study findings are partially contrary to Xu et al. [36] which posited a linear relationship between inflation and carbon returns. Our results indicate that, while inflation impacts emissions, the relationship exhibits variability across different contexts, contradicting the uniform linear impact suggested by Xu et al.

Moreover, the observed relationship between inflation rates and GHG emissions in the studied regions aligns with certain aspects of the EKC framework. For instance, in the USA and EU, emissions tend to decrease as inflation rises beyond specific thresholds (4.7% and 7.5%, respectively), indicating a transition towards lower-emitting activities due to economic pressures. On the other hand, China exhibits a more complex pattern, with two inflection points where emissions first decline sharply at 4.5% inflation, and then stabilize beyond 7% inflation, suggesting a multistage response to economic factors. While the EKC traditionally focuses on income levels, this study extends its applicability by showing that inflationary forces, closely tied to economic growth trajectories, can lead to similar results in emission patterns. The findings underscore the EKC theory's relevance in interpreting the complex relationship between economic policies and environmental outcomes.

The findings also indicate a critical tipping point where the balance between economic growth and environmental sustainability becomes unfavorable. This insight is vital for policymakers, who must weigh the environmental costs of inflationary policies and consider implementing countermeasures to prevent an increase in GHG emissions. In light of the nuanced relationship between inflation and GHG emissions demonstrated by the analysis, it is clear that central banks should not consider expansionary monetary policies as a straightforward mechanism for reducing GHG emissions. While it was found that there is a correlation between inflation and emissions, this does not directly translate into a causal pathway suitable for policy prescription. Therefore, we suggest that policymakers should prioritize integrated economic strategies that are environmentally aware rather than relying on inflation adjustments alone. Such strategies should be underpinned by a comprehensive understanding of the economic-environmental nexus, informed by empirical data and tailored to regional specificities. Thus, there is a pressing need for policymakers to distinguish between ephemeral emission reductions, spurred by economic downturns, and sustainable decreases resulting from deliberate policy initiatives and structural shifts towards greener practices.

In addressing the limitations of our study, it is important to note that the feedforward neural network model, optimized with the Levenberg–Marquardt backpropagation algorithm, inherently faces challenges such as potential overfitting, sensitivity to initial conditions, and dependency on the diversity of the training dataset. To mitigate these issues, we have employed a fivefold cross-validation technique. Moreover, further research is warranted to delve into the sector-specific ramifications of inflation on GHG emissions. Such studies should aim to dissect the intricate dynamics within various economic sectors, enhancing our understanding of how inflationary pressures differentially impact these sectors in terms of their environmental footprint. Additionally, an in-depth exploration of the policy frameworks that underpin the observed data patterns would be instrumental in formulating more targeted and effective environmental and economic strategies. This would not only enrich the existing body of knowledge but also provide a more granular perspective on the interplay between macroeconomic policies and environmental outcomes.

Conclusions

This study has analyzed the intricate relationship between inflation and GHG emissions in the USA, EU, and China, utilizing a robust methodological approach. The research employed feedforward neural network models, optimized with the Levenberg–Marquardt backpropagation algorithm, to predict GHG emissions based on inflation rates and fossil fuel energy consumption. The analysis of historical inflation data reveals distinct patterns in each region. The EU and USA displayed similar inflation trends until the late 1980s, with notable peaks during the 1970s linked to the global oil crisis. China's inflation landscape, starting in 1987, showed a more volatile pattern with dramatic spikes in the late 1980s and early 1990s, reflecting its transition to a market-oriented economy. The study's key findings include the identification of specific points where inflation rates correlate with changes in GHG emissions. In the USA, GHG emissions tend to decrease as inflation rates rise above 4.7%. The EU follows a similar trend, with emissions declining sharply after exceeding a 7.5% inflation rate. Notably, China exhibits two critical inflection points where GHG emissions start to decline at a 4.5% inflation rate and then stabilize after reaching 7%. A pivotal finding is the uniform increase in GHG emissions at a 4.4% inflation rate across all three regions, suggesting a common global economic behavior impacting environmental outcomes. This discovery underscores the need for globally coordinated economic and environmental policies. The study also highlights that while there is a correlation between inflation and GHG emissions, central banks should not solely rely on monetary policy adjustments to reduce emissions due to the complex relationship involved. Policymakers should adopt comprehensive strategies that focus on long-term environmental sustainability rather than short-term economic fluctuations. There is a pressing need for policymakers to distinguish between ephemeral emission reductions, spurred by economic downturns, and sustainable decreases resulting from deliberate policy initiatives and structural shifts towards greener practices.

As a final remark, it is recommended that future investigations explore how the relationship between inflation and GHG emissions progresses over time, considering economic cycles. This approach could provide a more dynamic understanding of their interplay.

Author contributions
Mutaz AlShafeey: Conceptualization, Methodology, Data acquisition, Analysis and interpretation of data, Writing-original draft; Saleh Saleh: Data acquisition, Analysis and interpretation of data, Writing-original draft.

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Availability of data and materials
Data are available from the corresponding author upon request.

Declarations

Ethics approval and consent to participate
The authors undertake that this article has not been published in any other journal and that no plagiarism has occurred.

Competing interests
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References

1. Ahmad M, Satrovic E (2023) How do fiscal policy, technological innovation, and economic openness expedite environmental sustainability? Gondwana Res 124:143–164
2. Dietz S, Stern N (2015) Endogenous growth, convexity of damage and climate risk: how Nordhaus' framework supports deep cuts in carbon emissions. Econ J 125(583):574–620
3. Ollivier QR, Maher DT, Pitfield C, Macreadie PI (2022) Net drawdown of greenhouse gases (CO2, CH4 and N2O) by a temperate australian seagrass meadow. Estuaries Coasts 45(7):2026–2039
4. Ocko IB, Hamburg SP, Jacob DJ, Keith DW, Keohane NO, Oppenheimer M, Roy-Mayhew JD, Schrag DP, Pacala SW (2017) Unmask temporal trade-offs in climate policy debates. Science 356(6337):492–493
5. Merbold L, Decock C, Eugster W, Fuchs K, Wolf B, Buchmann N, Hörtnagl L (2020) Memory effects on greenhouse gas emissions (CO2, N2O and CH4) following grassland restoration? Biogeosciences discussions
6. Annicchiarico B, Di Dio F (2017) GHG emissions control and monetary policy. Environ Res Econ 67:823–851
7. Krogstrup S, Oman W (2019) Macroeconomic and financial policies for climate change mitigation: a review of the literature
8. Avgousti A, Caprioli F, Caracciolo G, Cochard M, Dallari P, Delgado-Téllez M, Ferdinandusse M, Filip D, Prammer D, Schmidt K (2023) The climate change challenge and fiscal instruments and policies in the EU. ECB occasional paper (2023/315)

9. Steffen W, Rockström J, Richardson K, Lenton TM, Folke C, Liverman D, Summerhayes CP, Barnosky AD, Cornell SE, Crucifix M (2018) Trajectories of the earth system in the anthropocene. Proc Natl Acad Sci 115(33):8252–8259
10. Şener ŞEC, Sharp JL, Anctil A (2018) Factors impacting diverging paths of renewable energy: a review. Renew Sustain Energy Rev 81:2335–2342
11. Frankel JA (2008) Global environmental policy and global trade policy
12. IEA IEA (2022) CO2 Emissions in 2022. Paris
13. Ronaghi M, Reed M, Saghaian S (2020) The impact of economic factors and governance on greenhouse gas emission. Environ Econ Policy Stud 22:153–172
14. Ahmad W, Ullah S, Ozturk I, Majeed MT (2021) Does inflation instability affect environmental pollution? Fresh evidence from Asian economies. Energy Environ 32(7):1275–1291
15. Ullah S, Apergis N, Usman A, Chishti MZ (2020) Asymmetric effects of inflation instability and GDP growth volatility on environmental quality in Pakistan. Environ Sci Pollut Res 27:31892–31904
16. Musarat MA, Alaloul WS, Liew M, Maqsoom A, Qureshi AH (2021) The effect of inflation rate on CO2 emission: a framework for Malaysian construction industry. Sustainability 13(3):1562
17. Hamilton JD (2011) Nonlinearities and the macroeconomic effects of oil prices. Macroecon Dyn 15(S3):364–378
18. Bistline J, Blanford G, Brown M, Burtraw D, Domeshek M, Farbes J, Fawcett A, Hamilton A, Jenkins J, Jones R (2023) Emissions and energy impacts of the inflation reduction act. Science 380(6652):1324–1327
19. Grolleau G, Weber C (2024) The effect of inflation on CO2 emissions: an analysis over the period 1970–2020. Ecol Econ 217:108029
20. Sarker IH (2021) Machine learning: algorithms, real-world applications and research directions. SN Comput Sci 2(3):160
21. Alshafeey M (2023) Artificial Intelligence Forecasting Techniques For Reducing Uncertainties In Renewable Energy Applications. Budapesti Corvinus Egyetem
22. Li S, Siu YW, Zhao G (2021) Driving factors of CO2 emissions: further study based on machine learning. Front Environ Sci 9:721517
23. Hamrani A, Akbarzadeh A, Madramootoo CA (2020) Machine learning for predicting greenhouse gas emissions from agricultural soils. Sci Total Environ 741:140338
24. Ma N, Shum WY, Han T, Lai F (2021) Can machine learning be applied to carbon emissions analysis: an application to the CO2 emissions analysis using Gaussian process regression. Front Energy Res 9:756311
25. AlShafeey M, Rashdan O (2023) Quantifying the impact of energy consumption sources on GHG emissions in major economies: a machine learning approach. Energ Strat Rev 49:101159
26. Shakoor A, Ahmed R (2023) The environmental sustainable development goals and economic growth: an empirical investigation of selected SAARC countries. Environ Sci Pollut Res. https://doi.org/10.1007/s11356-023-30483-y
27. Rockström J, Bai X, DeVries B (2018) Global sustainability: the challenge ahead. Global Sustainability 1:e6
28. Purnell PJ (2022) A comparison of different methods of identifying publications related to the United Nations sustainable development goals: case study of SDG 13—climate action. Quant Sci Stud. https://doi.org/10.1162/qss_a_00215
29. Deaton A, Zaidi S (2002) Guidelines for constructing consumption aggregates for welfare analysis, vol 135. World Bank Publications, Washington, D.C.
30. Ahmad Q, Warrick RA, Downing T, Nishioka S, Parikh K, Parmesan C, Schneider S, Toth F, Yohe G (2001) Methods and tools. Climate change:105–143
31. Jones MW, Peters GP, Gasser T, Andrew RM, Schwingshackl C, Gütschow J, Houghton RA, Friedlingstein P, Pongratz J, Le Quéré C (2023) National contributions to climate change due to historical emissions of carbon dioxide, methane, and nitrous oxide since 1850. Sci Data 10(1):155
32. Sapna S, Tamilarasi A, Kumar MP (2012) Backpropagation learning algorithm based on Levenberg Marquardt algorithm. Comp Sci Inform Technol 2:393–398
33. Shoaib M, Raja MAZ, Zubair G, Farhat I, Nisar KS, Sabir Z, Jamshed W (2021) Intelligent computing with levenberg–marquardt backpropagation neural networks for third-grade nanofluid over a stretched sheet with convective conditions. Arab J Sci Eng. https://doi.org/10.1007/s13369-021-06202-5
34. Dissanayake H, Perera N, Abeykoon S, Samson D, Jayathilaka R, Jayasinghe M, Yapa S (2023) Nexus between carbon emissions, energy consumption, and economic growth: evidence from global economies. PLoS ONE 18(6):e0287579
35. Djedaiet A (2023) Does environmental quality react asymmetrically to unemployment and inflation rates? African OPEC countries' perspective. Environ Sci Pollut Res 30(46):102418–102427
36. Xu Y, Li X, Yuan P, Zhang Y (2023) Trade-off between environment and economy: the relationship between carbon and inflation. Front Environ Sci 11:334

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