Vol.65: e22210594, 2022
https://doi.org/10.1590/1678-4324-2022210594
ISSN 1678-4324 Online Edition

Review - Engineering, Technology and Techniques

Modeling of Brazilian Carbon Dioxide Emissions: a Review

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Editor-in-Chief: Alexandre Rasi Aoki
Associate Editor: Fabio Alessandro Guerra

Received: 27-Sep-2021; Accepted: 28-Dec-2021.

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HIGHLIGHTS

- The most used model types and independent variables to forecasting Brazilian CO_2 emissions can be obtained by literature review.
- Gray models and artificial neural networks are the most promising modeling methods.
- Economic growth and energy consumption are the main independent variables to forecasting Brazilian CO_2 emissions.

Abstract: Brazil is a signatory to the Paris Agreement and aims to reduce 43% of CO_2 emissions by 2030, compared to 2005. However, changes in energy policies are needed to achieve this goal, evaluating the produced effects on emissions. One way to predict these effects is through mathematical modeling. In this paper, we carried out a literature review to identify the most used model types and independent variables to forecasting Brazilian CO_2 emissions. The review showed that gray models and artificial neural networks are the most used ones. Furthermore, we also identified that economic growth and energy consumption are the main independent variables.

Keywords: Brazil; Paris Agreement; Greenhouse gases; Emissions modeling.

INTRODUCTION

Among the greenhouse gases (GHG) generated by anthropogenic causes, CO_2 represents 77% of total emissions in the world. Between 1970 and 2004, there was an increase of 80% in CO_2 emissions, from 21 to 38 gigatons [1]. It is highly likely that GHG concentrations, together with other anthropogenic forces, are responsible for more than half of the increase in the average temperature on the earth's surface between 1951 and 2010 [2]. Such an increase in CO_2 emissions becomes a worrying fact since the increase in the average temperature causes climatic changes. The fifth evaluation report of the Intergovernmental Panel on Climate Change – IPCC [3], presents the impacts and risks associated with these climate changes, including:

● Changes in hydrological systems due to changes in precipitation or melting of snow and ice.

● Changes in seasonal activities, habitats, migration patterns, species interactions, and the abundance of terrestrial freshwater and marine species.

● Risk of food insecurity and the collapse of food systems linked to heating, drought, and floods, particularly for the most impoverished populations in urban and rural environments.

● Due to extreme weather events, systemic risks lead to the collapse of essential infrastructure and services networks, such as electricity, water supply, and health and emergency services.

In the face of such a threat, the Kyoto Protocol was established in 1997 to reduce GHG emissions. However, the Paris Agreement established in 2016 was the first international climate agreement to establish mandatory mitigating actions for all countries [4]. To measure the performance of mitigating actions concerning global climate goals, accurate statistics for estimating CO_2 and other GHGs are essential. In addition, countries' ability to monitor and review emissions from their sources is essential in their involvement in national and global GHG mitigation, serving as a source of information for developing new policies and the carbon credit market [5]. CO_2 forecasts are also helpful to predict the possible environmental impacts caused by climate change, as in the case of Colombo and Joly [6]. They used the IPCC's climate change and CO_2 concentration scenarios to simulate changes in the distribution, and possible reduction, of tree species in the Atlantic forest.

Despite the diversity of studies focused on the prediction and characterization of CO_2 emissions, to our knowledge, there is no review work on the study of the forecast of Brazilian emissions. Thus, this paper presents a literature review focused on forecasting Brazilian CO_2 emissions. First, we search for papers from 1945 to 2020 on the Web of Science using “forecast of carbon dioxide emissions in Brazil” and “forecast of carbon dioxide emissions OR forecast of CO_2 emissions AND Brazil” assets of keywords. Next, the selected works were reviewed, registering the model used for CO_2 predictions, its advantages, and the possible limitations. Finally, papers related to CO_2 emissions in Brazil were selected, observing the models' performances and the relevant variables for Brazilian emissions.

Global CO_2 emissions

From 1990 to 2015, a significant increase in global CO_2 emissions from several sources was observed. Emissions caused by the burning of fuels increased by 56%, while those related to the production of fossil fuels and industrial processes grew by 32% and 102%, respectively [4]. As shown in Figure 1, the gas that most contributes to the increase in GHG supplies is CO_2, representing 73% of the global GHG statistics in 2015. In addition, we can see in Figure 2 that the main source of CO_2 emissions is the burning of fossil fuels [4].

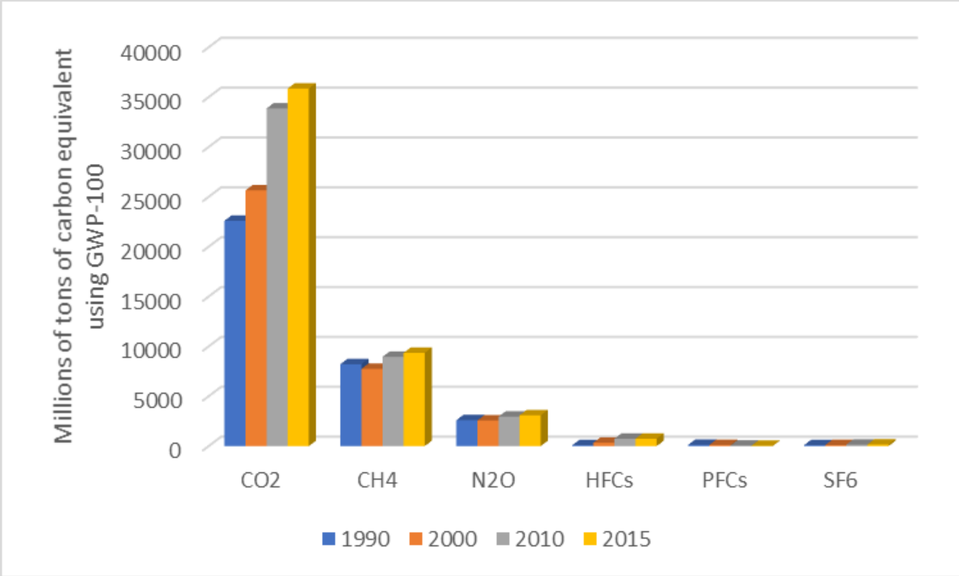

Figure 1. Worldwide emission of greenhouse gases in different periods. HFCs – Hydrofluorocarbons; PFCs-Perfluorinated compounds; GWP-100 - Global Warming Potential values for 100-year time horizon relative to CO_2. Source: Data obtained from the International Energy Agency [4].

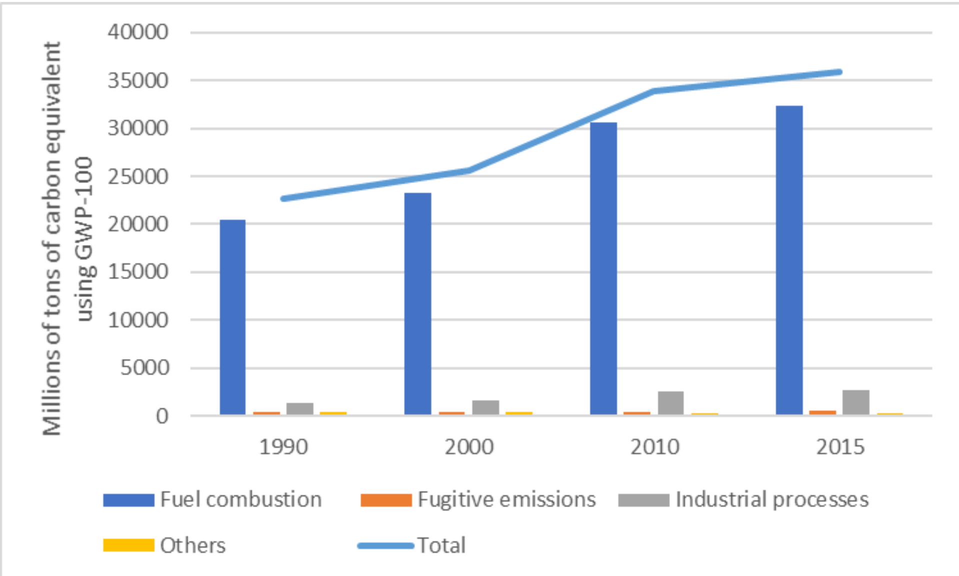

Figure 2. Emissions of carbon dioxide distributed by sources in different periods. GWP-100 - Global Warming Potential values for 100-year time horizon relative to CO_2. Source: Data collected from the International Energy Agency [4].

According to the International Energy Agency (IEA) data, in 2018, the total CO_2 emissions in the world reached 33.51 billion tons, with the electricity and heat production, transportation, and industry sectors being the most significant contributors [7]. In addition, data from Our World in Data shows that in 2019 the country with the highest CO_2 emission was China, emitting 10.17 billion tons, followed by the United States of America, with 5.28 billion tons, and India, with 2.62 billion tons [8]. However, except for a few countries such as China, India, and the USA, observing the data available at the IEA and Our World in Data does not make it possible to confidently assess the trends in CO_2 emissions, highlighting the importance of studies at forecasting CO_2 emissions.

In 2015, faced with the threats of climate change, 196 countries agreed to implement the Paris Agreement, which would come into force in December 2016. The Paris Agreement is an international treaty dedicated to combating climate change. Its main objective is to limit the increase in global temperature to less than 2 °C, compared to pre-industrial levels. Countries aim to reach the peak of GHG emissions as quickly as possible to limit the rise in global temperature. This increase means reaching the point at which emissions start to decrease, so CO_2 and other gas emission forecasts become helpful tools to identify whether countries are close to reaching that peak or not. The Paris agreement was not the first treaty to address the problem of climate change. In 1997 the Kyoto Protocol was created. Unlike its successor, the Kyoto Protocol does not aim at a common goal and only asks participating countries to adopt measures and policies to limit and reduce GHG emissions to achieve individual goals and report them periodically. For this, the protocol established rigorous monitoring, verification, and review [9,10].

Brazilian CO_2 emissions

According to data from Our World in Data [8], in 2019, Brazil presented an increase of 125.07% in CO_2 emissions compared to 1990, but a drop of 11.1% in relation to 2014. In 2019, Brazil was responsible for emitting 2.21 tons of CO_2 per capita, resulting in 465.72 million tons.

Given the importance of estimating CO_2 levels, some studies are dedicated to characterizing those supplied in Brazil. For example, Schulz and Ruppenthal [11] used the Box & Jenkins methodology for in-sample forecasts and defined emissions dynamics between 1960 and 2013. Réquia et al. [12] presented an approach for developing vehicle gas emission inventories focusing on municipal variations, making it possible to create specific mitigating actions and provide an alternative source of data for CO_2 emission forecasts. However, monitoring CO_2 emissions is not just about measuring the emitted values. It is also necessary to know the causes. As a result, studies aimed at understanding which factors impact CO_2 emissions. For example, Lima Filho, Aquino, and Nogueira Neto [13] analyzed the impacts of fuel price interventions on CO_2 emissions. Bildirici [14] analyzed the relationship between CO_2 emissions, economic growth, and militarization in Brazil, the United States of America, and China. Table 1 presents a compilation of the works related to the forecast of CO_2 emissions in Brazil.

Table 1. Revised works related to CO_2 emissions in Brazil and their observed advantages and disadvantages.

Reference	Model	Advantage	Disadvantage
[15]	Trend analysis	A simple model that can be used with the available data	It is limited to situations of linear behavior
[16]	Univariate gray prediction model	Possibility to represent complex systems with limited amounts of data	The performance of the model in comparison with other models depends on the database used
[17]	Regression for stationary samples, considering the possibility of structural breaks	The reliability of population growth predictions is high, same advantages as trend analysis	Limited to stationary situations
[12]	Top-Down approach for forecasting vehicle emissions in the period between 2001 and 2012	Alternative to obtain a more detailed emission distribution profile	Need a consistent database not only with emissions but also with generating mechanisms
[11]	Box & Jenkins, ARIMA (0,1,2), in-sample predictions	Able to model and predict the behavior of CO_2 emissions with non-stationary data. Arima model can validate the results obtained with other models	The variable, CO_2 emissions, is explained only by past values, without taking into account the interference of other factors
[18]	Artificial neural networks: Multilayer Perceptron with back-propagation	Efficient in dealing with non-linear, complex situations and with diffuse data. It is not necessary to know specific mathematical relationships between variables	Need to determine the number of neurons through trial and error
[19]	Conformable non-homogeneous gray fractional model	Possibility to represent complex systems with limited amounts of data	Low-performance results in cases of random, non-linear, or non-stationary data
[20]	Gray System Model	Possibility to represent complex systems with limited amounts of data	Limited to linear systems, but there are ways to deal with this limitation

[1] ARIMA - AutoRegressive Integrated Moving Average.

In Table 1, gray models are cited three times. The choice of this type of model is justified by its ability to represent complex systems with limited amounts of data. The gray model used by Pao and Tsai [16] is the univariate modeling of gray prediction, presenting a good performance when making predictions. The study indicated a strong relationship between CO_2 emissions, economic growth, and energy consumption.

Wu et al. [19] used different gray models to predict the CO_2 emissions in the countries that make up the BRICS from 2019 to 2025. In their study, data from these countries from 2000 to 2018 were used. Among the models used, the gray models of integer order have lower performance when compared to the fractional gray models. The model that presented the best result was the conformable fractional gray model CFNGM (1; 1; k; c), being *c* a parameter to be solved and *k* = 2, 3 ..., which successfully captured trends in Brazilian emissions. The CFNGM (1; 1; k; c) showed the best forecasting emissions for Brazil, India, China, and South Africa. However, the model did not show good results in forecasting Russian emissions. None of the models, integer or fractional, was able to identify the Russian emissions trend very well. This difficulty can be attributed to the random, non-linear, and non-stationary behavior of the data. The study by Wu et al. [19] predicts a reduction in the annual increase in Brazilian CO_2 emissions between 2019 and 2025.

Ahmed S., Ahmed K., and Ismail [20] used the gray model (1,1) and efficient multivariable model limited to linear systems. This limitation was bypassed using an algorithm based on error correction of non-linear gray models and applying the Kernel method. The authors estimated the short-term impact caused by technological innovations, economic growth, fossil fuel consumption, and renewable energy consumption in CO_2 emissions. Also, they observed that Brazil's CO_2 emissions are strongly associated with Gross Domestic Product (GDP), fossil fuel consumption, and renewable energy. When analyzing the growth of emissions considering these variables constant, an increase of 23% in Brazilian emissions is expected, while when treating CO_2 emissions as a factor dependent on these variables, the expected growth is 92%. The authors concluded that CO_2 emissions in Brazil decrease with the increase in the renewable energy sector, and in the short term, they also decrease with economic growth. However, they increase with the registration of technological patents of all types. The researchers suggest implementing renewable energy in the commercial and residential sectors to reduce Brazil's carbon footprints.

Another methodology for forecasting CO_2 emissions is trend analysis, a simple model used with the available data. Köne and Büke [15] applied the trend analysis to study the global CO_2 emissions and the twenty-five countries that emit the most. However, the model is limited to situations of linear behavior, which restricts the number of cases in which it can be applied. Fourteen of the twenty-five countries did not show a linear trend, and, therefore, a trend analysis was not carried out for them. The authors concluded that although the results are close to those predicted by the International Energy Outlook 2009, factors such as economic growth, political initiatives, technological advances, and fuel consumption must be considered for more accurate forecasts [15]. McKitrick, Strazicich, and Lee [17] also made use of trend analysis. However, they used two- and one-break Lagrange multiplier (LM) unit root tests to identify whether the data was stationary or not. After that, the authors proceeded with the regression. Unlike other studies, they used CO_2 emissions per capita, as the reliability of demographic growth forecasts for the coming decades is high. Therefore, the total CO_2 forecast using per capita forecasts is more reliable when compared to forecasts based on other variables such as GDP.

As noted, nonlinearity and non-stationary data influence the predictions' results, especially when using classical statistical models, such as regressions. Considering these factors, Acheampong and Boateng [18] decided to use artificial neural networks to carry out CO_2 emissions predictions, more specifically, the multi-layer Perceptron model with back-propagation. Neural networks are efficient in dealing with non-linear data, complex situations, and fuzzy information. Furthermore, it is not necessary to know specific mathematical relationships between variables. The results obtained by Acheampong and Boateng [18] proved to be promising, with negligible errors in the CO_2 emission forecasts of the countries studied, Brazil, the USA, Australia, India, and China. The main disadvantage observed in this method is determining the number of neurons through trial and error. Finally, Acheampong and Boateng [18] conducted a sensitivity analysis to identify the variables that most impact each country's emissions. For example, urbanization, research and development (R&D), and energy consumption are the most influential in increasing CO_2 emissions in Brazil. On the other hand, industrialization, economic growth, and foreign investment reduce emissions.

In addition to neural networks, Box & Jenkins models, generically called ARIMA, can be used to model and predict the behavior of CO_2 emissions with non-stationary data. Using data on CO_2 emissions in Brazil from 1960 to 2013, Schulz and Ruppenthal [11] proved through unit root tests that the data series is non-stationary and identified the AutoRegressive Integrated Moving Average (ARIMA) model (0.1, 2) as the one that best describes the time series of CO_2 emissions. However, ARIMA is a time series method in which CO_2

emissions are explained only by previous values, without considering other influencing factors. Therefore, this methodology is limited because factors influencing CO_2 emissions must be known to develop mitigating initiatives. After performing tests with the ARCH LM, Jarque Bera, and Bartlett methodologies, Schulz and Ruppenthal [11] concluded that the ARIMA model (0.1, 2) can predict future CO_2 emissions. Furthermore, results obtained by applying the ARIMA methodology can be used to validate the results obtained with other models.

Another model found in the literature was the top-down approach adopted by Réquia et al. [12], intending to predict vehicle gas emissions, including CO_2, at the municipal level. The importance of a consistent data source to monitor and study CO_2 emissions is undeniable. Many municipalities do not have a monitoring system. Therefore, the model presented by Réquia and coauthors [12] presents an alternative for using state and national monitoring data to obtain a more detailed emission distribution profile. The emissions profile allows for better planning of actions aimed at reducing CO_2 emissions. The methodology disadvantage is the need for a database consistent with the emissions and generating mechanisms, such as the number and type of vehicles. This need once again highlights the importance of understanding how and which variables influence CO_2 emissions.

The factors that impact the forecast of Brazilian CO_2 emissions are listed in Table 2.

Table 2. Main variables related to CO_2 emissions in Brazil and justification of the authors to work with these variables.

Variable	**Effect on CO_2 emissions**	**Justification**
Urbanization	Increase	The impact of urbanization is still in discussion. Some authors pointed out that modernization impacts the environment in favor of economic growth [18].
Research and Development (R&D)	Increase	R&D has the potential to lead to innovations in more sustainable energy sources, but it can also cause an increase in energy consumption [18].
Energy consumption	Increase	Energy consumption is one of the main factors responsible for CO_2 emissions [18].
Industrialization	Decrease	Industrialization implies growth in energy consumption and is strongly linked to the consumption of fossil fuels [18].
Economic growth	Decrease	Economic growth and energy consumption are related in a complex manner. Economic growth requires greater energy consumption but leads to more efficient consumption [16].
Foreign investment	Decrease	It is pointed out that foreign investors promote sustainable technologies while impacting economic growth [18].
Gross Domestic Product (GDP)	Unspecified individual effect	It is one of the factors considered by the empirical literature when making emission forecasts in developing countries [20].
Consumption of fossil fuels	Increase	Energy consumption, one of the main factors considered by the empirical literature when making emission forecasts in developing countries, is divided into fossil and renewable fuels [20].
Renewable energy	Decrease	Energy consumption, one of the main factors considered by the empirical literature when making emission forecasts in developing countries, is divided into fossil and renewable fuels [20].
Technology patents	Increase	Technological innovation helps develop new forms of renewable energy and helps to increase the efficiency and consumption of the forms of energy already employed [20].
Militarization	Unspecified individual effect	The military consumes large amounts of fuel due to various air, land, and sea vehicles [14].
Fuel price control	Situational	The transport sector is the main contributor to air pollution and emissions, resulting in the great importance of government policies to control vehicle emissions [13].

According to Table 2, militarization [14] and fuel price control policies [13] also influence Brazilian CO_2 emissions. Bildirici [14] considers the military the main source of GHG emissions in Brazil, the USA, and China. The relationships between militarization, economic growth, biofuels, and CO_2 emissions were studied through Autoregressive Distributed Lag (ARDL) causality tests and cointegration. The results found positive correlation coefficients between CO_2 emissions and economic growth, between CO_2 emissions and militarization, and CO_2 emissions and biofuels consumption in Brazil. Furthermore, according to Bildirici [14], there is evidence of a long-term cointegration relationship between the four studied variables. Nevertheless, the militarization impact on CO_2 emissions and biofuels consumption in Brazil is smaller than that observed in China and the USA.

Fuel price control policies are also an essential factor to be analyzed since Brazil has a considerable portion of its fleet of vehicles adapted for the use of ethanol, a less polluting and renewable source fuel. However, the use of this fuel is influenced by the price of petroleum-based fuels. For example, Lima Filho, Aquino, and Nogueira Neto [13] pointed out that from 2009 to 2016, Brazil's price of fossil fuels was below inflation. Meanwhile, the price of ethanol has gone up, which has resulted in a decrease in its use. Therefore, the authors believe that the fuel price intervention policy adopted between 2011 and 2014 had a considerable impact on CO_2 emissions. As a result, the increase in emissions was 32.84%. Meanwhile, in the scenario where such a policy was not employed, the expected increase would be 18.33%, a significantly smaller amount.

CONCLUSION

Global warming is a growing concern on the international stage. Climate change has started to be observed and brings several threats to the environment. Therefore, the Paris agreement established mitigating actions for all countries. CO_2 emissions are considered the leading cause of the increase in the average temperature of the planet. For this reason, the elaboration of policies and actions aiming to reduce such emissions is fundamental. Thus, it is necessary to constantly monitor such emissions and study their causes and historical behavior to predict future values to measure the actions' effectiveness. This study sought to analyze the methods already applied in forecasting CO_2 emissions in Brazil. We investigated the advantages and limitations of each method and identified the possible variables correlated with Brazilian CO_2 emissions.

Different types of models are used in forecasting CO_2 emissions. The gray models and artificial neural networks showed the most promising results, mainly due to their ability to represent complex, non-linear, and, in some cases, non-stationary systems. Despite presenting consistent results, trend analysis models are limited to stationary and less complex systems. Furthermore, trend analysis has limited application because it only considers past values of CO_2 emissions to make predictions. The same problem was observed when we investigated the Box & Jenkins model. Despite this, the Box & Jenkins model is not limited to stationary situations and has shown excellent results in in-sample forecasts, which opens up the possibility of being used comparatively with other models.

A relationship was observed between several variables and CO_2 emissions, with economic growth and energy consumption being the most relevant. The first presents evidence of reducing Brazilian CO_2 emissions, while energy consumption seems to increase. However, energy consumption is a better-analyzed variable when observing the effects of different types of energy consumed. For example, while renewable energy consumption reduces CO_2 emissions, fossil fuel consumption implies an increase. Furthermore, the increase in the consumption of fossil fuels occurs when price intervention policies favor their use over renewable fuels.

Funding: This study was financed in part by the Fundação de Amparo à Pesquisa do Estado da Bahia (FAPESB).
Acknowledgments: The authors would like to thank Fundação de Amparo à Pesquisa do Estado da Bahia (FAPESB) for supporting the research.
Conflicts of Interest: The authors declare no conflict of interest.

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